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How to incorporate temporal change in digital business research: The use of process theory and agent-based modeling

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ABSTRACT

Research on digital businesses builds upon a well-established set of theories, models, and frameworks. A frequently used approach within the paradigm of common variance theory is to first create a theory-based model and then test it using a multivariate method. Cross-sectional data is often used to test the overall fit of the model and the significance of its parameters, yet this approach fails to take into account the important role of temporal dynamics and the potential change of parameters over time, which constitutes an important research gap. For example, the popular Technology Acceptance Model (TAM) provides a snapshot in time, but cannot explain the postulated temporal patterns of the Diffusion of Innovations (DOI) theory. In this exploratory paper, we call for a theoretical and methodological paradigm shift and introduce process theory as a complement to the popular variance theory. This theory considers how entities change over time and create important network effects. Additionally, we illustrate how agent-based modeling (ABM) in combination with Structural Equation Modeling (SEM) can help to create models that combine the rigor of multivariate statistical methods with the capability of process theory to account for changes over time. Using ABM within the process theory paradigm can help to create meaningful models that are capable of incorporating temporal dynamics.

1. Introduction

The creation, adaptation, modification, testing, and validation of theories is a major goal of many academic disciplines (Ahmed & MacCarthy, 2022; Gregor, 2006; Hanafizadeh, Hatami Lankarani, & Nikou, 2022; Rivard, 2014; Truex, Holmström, & Keil, 2006). Not surprisingly, a substantial amount of academic literature builds on theory and gives epistemological and methodological advice on how to develop new theories and models (Roberts & Grover, 2009). An even larger body of literature deals with testing and refining these theories and models in order to advance the discipline. A common classification of primary theory objectives differentiates between four major goals: analysis and description, explanation, prediction, and prescription (Gregor, 2006). Over the years, a well-established pattern of theory testing has emerged in leading journals across disciplines (Gregor & Klein, 2014): Based on an established theory, research models are developed that consist of a number of hypotheses. This modeling process can be done with or without modifications and adaptations of the underlying theory. Causal effects are assumed based on logical reasoning, and the testing process usually includes the application of a multivariate statistical technique

such as Structural Equation Modeling (SEM) (Treiblmaier, Bentler, & Mair, 2011). This method is capable of simultaneously assessing both the measurement and the structural model, with the latter representing the proposed hypotheses (Bagozzi & Yi, 2012). Such an approach, however, does not take into account the relevance of processual components or, in other words, changes that occur over time and might alter the strength of causal relationships between the respective components.

We postulate that the results of all models that are tested with cross-sectional data are inevitably static. Therefore, any conclusions that can be reached pertain only to a specific point in time and may not sufficiently support the goal of creating generalized statements that are independent of time and space. In order to achieve general acceptance using a falsificationist approach (Popper, 1962), various attempts need to be made to check if a particular theory stands the test of time. Alas, each of these attempts will also be static (i.e., refer to a specific point in time) and it is hard to validate them against volatile real-world data. Even if a hypothesis or an entire theory is falsified, it remains unclear whether this actually indicates a lack of causality or is merely happenstance (Treiblmaier, 2019). Such issues would not necessarily be a cause for major concern if the theories themselves were static and implied that

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the postulated relationships between the constructs or entities remain stable over time and are not changed by factors that are external to the model (e.g., network effects). However, we argue that many theories used in technology-oriented research inherently contain numerous processual elements and that they assume and/or imply change over time that is caused by the direct interaction of entities. Such entities will frequently be human beings, but might also include organizations or even geographic locations. This processual nature is ignored whenever a static methodological approach is used. Consequently, its validation against cross-sectional data is complicated and potentially misleading. Furthermore, such approaches fail to exploit the full potential of academic research. This is in line with the recommendations from Venkatesh, Sykes, Aljafari, and Poole (2021), who lament that “limited research in [information systems] has incorporated a rich conceptualization and/or discussion of time.” Consequently, the authors urge researchers to enrich their research by incorporating time into their theories and study designs.

Niederman (2021, p. 14) summarizes the shortcomings of relying on static procedures using two popular theories: “Consider TAM and UTAUT [Unified Theory of Acceptance and Use of Technology]. [...] Nor is there embedded in the theory a feedback loop since, obviously, actual use should influence ease of use (if one comes down a learning curve) or perceived [usefulness] if one learns that the technology [...] will never perform well.” Furthermore, he highlights the importance of addressing temporal change: “a dynamic theory would address mutual influence of variables where each is both independent and dependent and how they change together over time” (p.14). We consider the widespread failure to apply dynamic theories and test them with dynamic methods to be an important research gap and pose our main research question:

How can theory-based digital business research incorporate temporal change?

To answer this question, we propose process theory as a proper theoretical foundation for “dynamic” (i.e., time-variant) approaches and suggest agent-based modeling (ABM) as one exemplary method to investigate such time-dependent patterns in combination with SEM. We explicitly acknowledge that most of the commonly used “static” approaches are valuable and help to advance the methodological foundation of the academic community. However, we second the suggestion from Niederman (2021) that process theory should be perceived as a complement to the dominant variance theory to further enrich research outcomes.

This paper is structured as follows: In section 2, we review and summarize the existing literature relating to the use of process theory and ABM. In section 3, we contrast the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DoI) theory¹ according to their handling of time. In section 4, we discuss the implications of processual elements and show how the TAM can be remodeled as a processual and recursive model. In section 5, we simulate how ABM can be used to integrate model dynamics and illustrate how a system’s state changes over time. In section 6, we summarize our approach and discuss several theories that are “inherently dynamic.” We end this paper with a brief discussion of how our approach can be used to apply new methods of validation (section 7), as well as addressing several limitations and providing suggestions for future research (section 8).

2. Literature review

Incorporating change elements into research projects requires the capacity to rethink the underlying theoretical paradigm. Most published empirical research relies on variance theory, which makes the value of dependent variables contingent on the value of independent variables.

¹ In this paper, we do not explicitly differentiate between the terms “theory” and “model.” The distinction between those two terms frequently becomes blurred (Blaikie, 2009) and is not of relevance for the overall goal of this paper.

In contrast, process theory explains the outcomes of interest by investigating a sequence of events, including time as an important component (Mohr, 1982). A shift in the underlying theoretical mindset toward process theory also impacts the epistemological foundation. According to Crowston (2000, p. 149), “process theories can be a useful milieu for theoretical interplay between interpretive and positivist research paradigms.” Relatively few researchers so far have explicitly stepped out of the prevailing paradigm and recognized that the current procedure of testing theory is inherently static and therefore limited in what it can achieve. Examples include Schubring, Lorscheid, Meyer, and Ringle (2016), who reflect that “PLS [partial least squares]-SEM results are to some extent static in that they usually build on cross-sectional data” (p. 4604), and Schwarz and Ernst (2009), who demonstrate how the inclusion of parameter estimates from SEM and regression analysis can better explain the diffusion of environmental innovations.

In Table 1, we list several prominent articles that discuss or exemplify the use of process theory in academic research with a focus on technology. The selection of the articles was based on a narrative literature review performed in September 2022 in which we searched several databases (e.g., EBSCO host, Scopus, Google Scholar) to identify seminal papers that incorporate process theory in their research. The initial search term was “process theory” and we extended our pool of papers using a snowballing approach to include relevant literature that was mentioned in the selected articles. This list does not include the popular dual process theory that builds on the assumption that knowledge can be gained from central and peripheral evaluation since these models are regularly assessed using cross-sectional data (e.g., Fadel, Meservy, & Jensen, 2015; Meservy, Jensen, & Fadel, 2014; Turel & Qahri-Saremi, 2016; Yan Chen, Deng, Kwak, Elnoshokaty, & Wu, 2019).

Building on related research in other fields (Markus & Robey, 1988; Mohr, 1982), Crowston (2000) suggests that using process theory can help researchers to better understand how organizations accomplish their goals and transform inputs into outputs. Marshall, McKay, and Prananto (2005) build on the process model suggested by Soh and Markus (1995) and use qualitative interviews with CIOs from large organizations to scrutinize the practices and processes that help to create business value through IT investments. Lind and Goldkuhl (2006) identify the need for different theories and develop a multi-grounded (i.e., empirically, internally, and theoretically founded) business process theory based on both inductive and deductive approaches. They highlight that this theory provides support for practical problem solving. Sooklal, Papadopoulos, and Ojiako (2011) illustrate how social processes impact the systems development process. They apply normalization process theory and present findings from a case study that illustrate how this theory can help in exploring the social production and organization of new practices. Their study also stresses the importance of stakeholder action. In her conceptual paper, Avgerou (2013) creates awareness regarding the importance of causality in explanatory research and outlines the social mechanisms that function as components of causal process theory. By tracing these social mechanisms, more complete and novel explanations of socio-technical phenomena can be gained. Fan, Lederman, Smith, and Chang (2014) delve deeper into the topic of how variance and process theories can be combined to get a more complete picture. They explicitly focus on trust formation in online health communities and develop a dynamic process theory of trust formation. They explain the dynamic progression between various states and illustrate how trust is developed through several processes. Tan, Pan, Xianghua, and Huang (2015) use a case study approach to illustrate how a process theory of multi-sided platforms can improve understandings of platform development, noting that organizational capabilities as well as the outcomes of platform development can differ between the various stages. Differentiating between various phases of cyber projects allows Moody, Kirsch, Slaughter, Dunn, and Weng (2016) to develop a process theory pertaining to the control of cyber projects that depicts how control evolves over time and is exercised in different stages of cyber projects. In a similar manner, Huber, Kude, and Dibbern

(2017) illustrate that the governance of platform ecosystems is a process that varies considerably and that changes in the rules and values can occur over time. To properly account for these changes, they suggest a process model that explicitly considers temporal changes. In their investigation of why employees do not comply with mandated information security behaviors, [Karjalainen, Sarker, and Siponen \(2019\)](#) point out that explanations for why individuals engage in different security procedures are not static but rather change over time as they face tensions or conflicting demands. [Niederman \(2021\)](#) provides a comprehensive summary of process theory, details the different streams of process research in information systems, and highlights its benefits. He considers process theory to be an essential part of the existing body of knowledge and recommends that it should be “nurtured and expanded” (p. 3). [Aaltonen, Alaimo, and Kallinikos \(2021\)](#) develop a process theory of data commodification in which the management and interpretation of data is linked to the portability, editability and recontextuability of digital data. Finally, [Zhang, Lee, Yoo, and Choi \(2022\)](#) develop a methodological framework based on critical realism principles for the construction of process theories and illustrate the usefulness of their approach using collaboration patterns on Wikipedia as illustrative examples.

Hitherto, ABM had been used relatively infrequently in leading digital business and information systems research journals, but interest has steadily grown in recent years, as can be seen by an increasing number of publications in top-tier journals (see the findings from a narrative review in [Table 2](#)). Existing research also illustrates the broad range of topics in which this method can be applied to simulate the interactions between agents in a system.

Table 1
Process Theory Examples.

Goal	Outcome	Source
Combining phenomena and theories from different levels of analysis.	Identification of processes that help organizations to reach their goals.	Crowston (2000)
Creating a process theory of IT governance.	Design of a model that shows IT processes and IT governance structures.	Marshall et al. (2005)
Developing a business process theory.	Presentation of a business process theory that aids business modelers.	Lind and Goldkuhl (2006)
Assessing the applicability of normalization process theory.	Confirmation of the pertinence of normalization process theory.	Sooklal et al. (2011)
Generating explanations in process research that draw from social theory.	Development of comprehensive causal explanation.	Avgerou (2013)
Exploring trust development in online health communities.	Extension of trust variance theories into hybrid process theories.	Fan et al. (2014)
Investigating how the capabilities of a sponsor can impact platform development.	Derivation of a process theory for platform development.	Tan et al. (2015)
Examining how control is exercised in cyber projects.	Development of a process theory of control in cyber projects.	Moody et al. (2016)
Investigating ecosystem-wide governance and the change of governance practices.	Development of a process theory about the success of ecosystem-wide governance.	Huber et al. (2017)
Understanding the change processes in different contexts.	Explanations for individuals' behavioral changes over time.	Karjalainen et al. (2019)
Establishing process theory as an alternative to variance theory.	A summary of process theory and a plea for its use in research.	Niederman (2021)
Developing a process theory that explains data transformation.	Insights on data management practices.	Aaltonen et al. (2021)
Creating a framework to develop process theories on routines.	Framework validation through the investigation of collaboration patterns.	Zhang et al. (2022)

[Valluri and Croson \(2005\)](#), for example, use ABM to model the performance of a supplier selection model that incorporates a complex reward and punishment scheme under incomplete information and illustrate the convergence to equilibrium when a single buyer interacts with a heterogeneous group of sellers. [Canessa and Riolo \(2006\)](#) investigate the impact of various computer-mediated communication modes on organizational culture and performance. Using ABM, they find that cultural development as well as performance are contingent on the communication mode and the duration of the communication period. Furthermore, the authors contrast ABM with empirically based research (e.g., survey studies) to unravel the benefits and limitations of the respective approaches. They especially highlight the utility of ABM in performing controlled experiments and in studying system dynamics. [Druckenmiller and Acar \(2009\)](#) explore the applicability of ABM to bridge qualitative and quantitative research approaches and strive to find a way to perform causal modeling with expert knowledge. Their study illustrates how the combination of various tools enables user-friendly interfaces to develop simulation models and scenarios. [Ahn \(2010\)](#) is interested in how online purchase processes can be optimized and combines ABM and evolution strategy to evaluate specific customer aid functions. He concludes that this approach can be used to evaluate functions under various assumptions and that this approach offers substantial benefits over tests or experiments that involve human participants. In their study on the impact of e-marketplaces on supply chain operations, [Zhang and Bhattacharyya \(2010\)](#) apply ABM with the use of an experimental design and highlight the applicability of the method to model the behavior of individual agents within complex supply chains.

[Nan \(2011\)](#) illustrates the potential of ABM to model emergent behavior in a study on how collective-level IT use patterns emerge as a consequence of individual-level behavior. She develops a complex adaptive systems model of IT use and concludes that her model provides the foundation for a new theory for conceptualizing IT use processes. Another example to highlight the usefulness of ABM to model complex supply chain processes stems from [Long and Zhang \(2014\)](#), who develop an integrated framework for agent-based, inventory-production-transportation modeling as well as a distributed simulation of a supply chain. They further illustrate the usefulness of their approach through a case study. The capability of ABM to account for nonlinear dynamics is leveraged by [Nan and Tanriverdi \(2017\)](#) to outline a theory that considers the role of IT in inducing nonlinear dynamics that afford new business strategies. The authors point out that this perspective creates a bridge to integrate a new generation of strategy insights into traditional firm-centric information systems strategies. [Zhang, Adomavicius, Gupta, and Ketter \(2020\)](#) strive to understand the temporal dynamics of recommender systems' performance by using ABM to assess the performance under various conditions, which would not be possible in the real world. Their results not only provide concrete recommendations for the design and implementation of recommender systems, but also highlight the usefulness of ABM to better understand the temporal dynamics of complex systems. Another related study comes from [Zhang, Chen, and Lyytinen \(2020\)](#), who explore principles of business and IT alignment and apply ABM to confirm the relevance of these principles for coevolutionary processes, namely mutual communication, knowledge sharing, and intelligence. [Gopal, Karmegam, Koka, and Rand \(2020\)](#) build on the resource-based view in combination with ABM to investigate whether it might be beneficial for IT service providers to move along the supply chain to gain a competitive advantage. They especially identify the conditions under which such a move might actually benefit a company. [Haki, Beese, Aier, and Winter \(2020\)](#) assess the evolution of information systems architecture in different organization types. Through various experiments they confirm the importance of coercive, normative, and mimetic pressures as well as their interplays in shaping the evolution of architectures. Finally, [Mueller-Bloch, Andersen, Spasovski, and Hahn \(2022\)](#) apply ABM to investigate how different parameters impact decentralization in proof-of-stake blockchains. Their findings create a better understanding of the underlying

governance mechanisms of blockchains and support the design of systems that are prone to decentralization. Taken together, previous applications of ABM in technology-oriented research not only illustrate the versatility of the method, but also make it clear that it can be used in combination with existing theory and also for theory generation. Furthermore, ABM particularly enables researchers to better understand and predict changes in processes over time.

3. Comparing static and processual models

Theories that can be tested with multivariate statistical methods are frequently portrayed as models that arrange various constructs in a nomological network, which implies presumed causal relationships. We define a theory as being “static” when all the hypothesized influencing factors are simultaneously shown in the model, boundary conditions are assumed (Busse, Kach, & Wagner, 2017), and the model parameters do not change over time. In other words, in such models no timeline or feedback loops exist and the outcome is only affected by processes that are shown in the causal relationships. Contrariwise, time plays a major

Table 2
ABM examples.

Goal	Outcome	Source
Assessing the performance of a supplier selection model.	Documentation of dynamic processes and equilibrium convergence.	Valluri and Croson (2005)
Examining the impact of computer-mediated communication modes on organizational culture and performance.	The development of organizational culture and performance depends on the communication mode and duration.	Canessa and Riolo (2006)
Studying the relevance of group support systems for strategic management processes.	Creation of a prototype for situation formulation.	Druckemiller and Acar (2009)
Evaluating customer aid functions of internet stores.	Personalized pages are not always the best customer aid function.	Ahn (2010)
Examining the impact of e-marketplaces on supply chain operations.	Supply network agents in e-marketplaces keep more inventory and lose fewer orders.	Zhang and Bhattacharyya (2010)
Exploring properties and mechanisms of information technology use patterns.	Collective-level IT patterns emerge from individual-level behavior.	Nan (2011)
Modeling and simulating supply chains.	A class library and a multi-agent distributed platform for supply chains.	Long and Zhang (2014)
Understanding the role of IT as a source of competitive advantage and a creator of hyperturbulent environments.	A theory that considers IT's role in inducing nonlinear dynamics and affording new business strategies.	Nan and Tanriverdi (2017)
Understanding longitudinal dynamics of recommender systems' performance.	In the long run, users' reliance on a recommender system makes the system less useful.	Zhang, Adomavicius, et al. (2020)
Validating coevolutionary principles of business and technology alignment.	Three coevolutionary principles exert positive effects on business and technology alignment.	Zhang, Chen, and Lyytinen (2020)
Evaluating the potential of IT service providers to gain competitive advantage.	Moving along the supply chain is risky for IT service providers but can occasionally be beneficial.	Gopal et al. (2020)
Examining the evolution and outcomes of information systems architecture.	Demonstration of the significance of different types of evolutionary pressures.	Haki et al. (2020)
Understanding decentralization of decision-making power in proof-of-stake blockchains.	Insights into blockchain governance mechanisms	Mueller-Bloch et al. (2022)

role in process theories, wherein the respective outcomes directly depend on the specific temporal status of the model. In the remainder of this paper, we will illustrate our rationale using the so-called network effect, which states that the value of an object to a specific individual is partially determined by the behavior or attitudes of other members within a particular group (Shapiro & Varian, 1998). Previous research has confirmed that the network effect exerts a major influence on individuals' decisions to adopt an innovation or to buy a specific product (Katona, Zubcsek, & Sarvary, 2011; Lee & Mendelson, 2007; Peng, Fan, & Dey, 2011).

3.1. Time-invariant adoption patterns

Downes and Nunes (2013) wrote that “big-bang disruptions don't follow the usual pattern of customer adoption famously described by Everett Rogers” (p. 47). We argue, however, that this is not the case. The authors contrast the adoption model of Rogers, which resembles a normal distribution, with their “new model,” which is also normally distributed. The only difference between the two cases is the respective standard deviation, which signifies the time needed for an innovation to receive public attention. The actual *pattern*, which consists of the shape, center, and spread of the distribution, is a normal distribution in both cases wherein just the spread (i.e., the standard deviation) differs. Using a different time scale on the abscissa would therefore result in identical patterns. To provide another example: In 1747, James Lind started his research with the goal of finding a cure for scurvy. It took him more than forty years before his seminal results were finally introduced in the Royal Navy (Bown, 2003). Modern internet memes and viral marketing campaigns, albeit far less important, achieve the same impact (i.e., reach) in a small fraction of the time (Ewing, Stewart, Mather, & Newton, 2014). In both cases, however, the classic bell-shaped (i.e., approximately normally distributed) adoption curve as postulated by Rogers (2003) is still prevalent. It is just the case that in the internet age, the average time span needed to complete the adoption process is drastically reduced. Given the strikingly similar adoption patterns, the question arises as to whether this temporal pattern can and should be incorporated into theories and models. If so, how this can be achieved needs to be determined since static models and testing procedures are not suitable to achieve this goal.

3.2. Time-variant adoption patterns

Fig. 1 illustrates our point by contrasting two widely used models that are popular in numerous research communities. The (core) TAM on the left represents a static view, which means that it does not explicitly include a temporal component. This parsimonious model shows how the constructs “Perceived Ease of Use” (PEOU) and “Perceived Usefulness” (PU) impact an individual's “Behavioral Intention to Use” (BIU) and subsequently the actual system use (Davis, Bagozzi, & Warshaw, 1989). The TAM does not include any temporal component. In contrast, the innovation adoption curve from Rogers (2003), which originates in his research on crop adoption and was originally published in 1962, has an explicit timeline and shows the number of users who adopt a certain innovation at a specific point in time. It is noteworthy that research on the TAM was inspired by Rogers' adoption curve as well as the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991). All of these theories are prevalent in academic research and are regularly tested with survey data by using a cross-sectional sample (Floh & Treiblmaier, 2006; P. J. Hu, Chau, Sheng, & Tam, 1999). Various extensions and modifications exist, all of which share the same core constructs – PEOU, PU, BIU – and occasionally also include the actual use of the innovation (Alnemer, 2022; Liu, Henseler, & Liu, 2022; Venkatesh, Morris, Davis, & Davis, 2003). Since actual use needs to be measured in a separate survey in order to fully account for the proposed causal relationship between BIU and actual use (which includes a temporal component), its measurement is frequently left out,

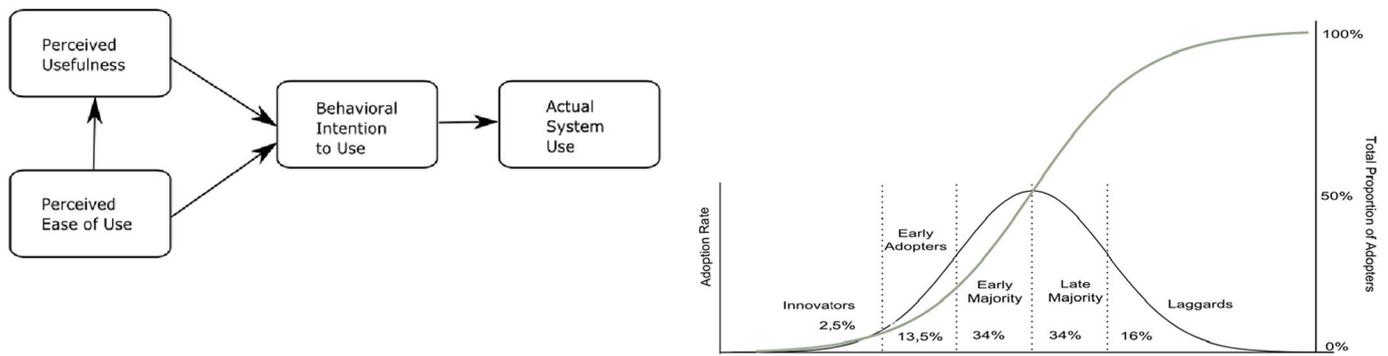


Fig. 1. Static and Processual Views on Technology Adoption (left; Davis et al., 1989) and Innovation Diffusion (right; Rogers, 2003).

and BIU becomes the dependent variable.

When comparing these two models, their respective objectives are straightforward. The TAM (shown on the left in Fig. 1) and its manifold modifications strive to determine the reasons why a certain technology is or is not adopted by (potential) users. Since these models are usually tested using cross-sectional data, they provide a snapshot in time. In contrast, the DoI theory does not deal with the *adoption rationale*, but rather includes a timeline that highlights a temporal *adoption pattern*. This general pattern is assumed to hold independent of the type of innovation or of individuals' attitudes, perceptions, motivations, and the like. Individuals are frequently categorized depending on their adoption date into innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003). As shown in the right part of Fig. 1, the cumulative adoption curve can be represented by a sigmoid function showing the typical "S" shape. Adoption rates initially increase until they reach a point of inflection from which they continue to decrease until a level of saturation is reached. A longitudinal survey study of innovation adoption that accounts for adoption motives is feasible, but it is also cumbersome and usually restricted to gathering data at discrete points in time (Mustonen-Ollila & Lyytinen, 2003).

Given their respective goals, we argue that the TAM and the DoI theories are highly complementary and combining them with the help of corresponding methods, namely SEM and ABM, will give researchers new insights that are not possible to achieve when applying them individually. SEM can be used to measure the strengths of the relationships between various endogenous and exogenous variables at a specific point in time, and, given this information, ABM can then be applied to predict how the overall system behavior changes. We therefore formulate and briefly explain five research postulates:

- (1) Enriching static theories with processual elements will help to estimate a system's time-dependent conditions.

The results that we get from a cross-sectional study only represent a snapshot in time. If we assume that the network effect holds, then the present impact of EOU and USE depends on the current number of users/adopters in a certain setting. Including processual elements in an adoption model will allow us to assess the level of PEOU and PUSE contingent on the current number of users.

- (2) Enriching processual theories with static elements will help to explain specific patterns.

A DoI model by itself is not capable of explaining why a specific innovation is adopted. As we have outlined above, it postulates a common pattern that is independent of the type of innovation and users' individual characteristics. It cannot explain, however, the actual speed of innovation, which, in turn, might be influenced by many of the constructs that are extensively discussed in the extended TAM literature (e.g., hedonic motivations, expectancies, or social influence). Including

such explanatory elements will help to better understand the duration of the adoption cycle or, in other words, determine the time until saturation is reached.

- (3) A combination of variance and process theory will help to improve descriptions, explanations, predictions, and prescriptions.

Description, explanation, prediction, and prescription are four central objectives of academic theories, all of which can be enhanced by combining variance and process theories. If we feed two given values for EOU and USE into a processual model, the system will be able to change its state iteratively until a certain stop criterion is reached. Conversely, if we know the current relevant system parameters, this will allow us to determine the system's state at a previous point in time. Finally, the modification of parameters might help us understand which parameters need to be targeted to achieve a certain adoption rate.

- (4) A combination of variance and process theory will facilitate new forms of validation.

Creating valid theories and models is one of the supreme goals of empirical research. Ultimately, this requires validating models against real-world data, which is hard to do with process theories and models depending on temporal effects. Given a network effect, PEOU and PUSE change over time, while all other factors remain constant. This implies that it is not possible to exactly determine the precise parameters of a TAM using real-world adoption data collected at a specific point in time and via the application of a multivariate statistical technique. The same holds true for every variance theory in which dynamic phenomena, such as a network effect, exist latently. Including processual elements will allow for validation against real-world data at specific points in time.

- (5) Many theories that are currently used in behavioral academic research are inherently processual and recursive.

We posit that many social science theories used to investigate digital businesses are inherently processual and potentially recursive and include some kind of network effect or similar phenomena that impact the model parameters over time. As such, using only a snapshot of cross-sectional data provides only a limited picture of the dynamic processes that are inherent in the model.

4. Creating processual and recursive models: the example of TAM

Previous research points out that the TAM is closely related to Ajzen and Fishbein's Theory of Reasoned Action and Theory of Planned Behavior, which are in turn based on the work of Rogers (Mathieson, 1991; Weigel, Hazen, Cegielski, & Hall, 2014). As outlined above, the

model from Rogers provides a longitudinal perspective without specifying the causal reasoning for adoption or non-adoption. The TAM (and its manifold modifications) provides a snapshot analysis that takes individual reasoning into account but does not facilitate predictions about adoption rates at specific points in time. Such predictions would allow for validity testing by making comparisons with real-world data. Fig. 2 shows how time-dependent model effects, which can be explained by the existence of network effects, may change individuals' perceptions of an innovation's attributes. For the sake of simplicity, we assume that all individuals have the same initial perception and that the network effect applies equally on all of them. Two different innovations (IN₁, IN₂) are shown at times t₀ and t₁. IN₁ (i.e., innovation 1) is not adopted by any of the three individuals (P₁, P₂, P₃) at t₀ as it lies below their respective adoption thresholds (TH), which are modeled as the sum total of PEOU and PUSE. IN₂, however, is adopted by P₁ at t₀ since it lies above that individual's threshold. This adoption by P₁ has implications for other individuals at t₁. Due to the network effect, the perceived EOU and USE increase for P₂, who now also decides to adopt. In this scenario, the "absolute" level of EOU and USE of the innovation did not change, but the network effect led to an increase in the perception of EOU and USE between t₀ and t₁, which, in turn, led to the adoption of IN₂ by P₂ at t₁.

Fig. 2 illustrates that PEOU and PUSE are by no means static attributes of an innovation (which is the way in which they are commonly treated), but rather dynamic attributes of an individual that can change over time. If the adoption curve of Rogers and the network effect hold, both of which have been confirmed by a substantial amount of literature, then the two main constructs of PEOU and PUSE are highly time-dependent. Even if the innovation's attributes (EOU, USE) do not change, the mere fact that other people are using it will lead to a more positive perception on the part of potential users. Consequently, the construct of a "subjective norm" is used to account for the pressure exerted by peers to adopt a specific innovation with measurement items phrased as follows: "Other people think that using [...] is important to me," "Many of the people I know expect me to [...] use...," and "Others would probably make me feel guilty if I quit using..." (Choi & Chung, 2013). However, this approach to incorporating social influence, which can be defined as the "degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. (2003), p. 451), does not fully account for different variants of network benefits since some of these benefits might not only be based on "peer pressure," but may also result from the fact that more people are adopting the innovation. Social influence therefore does not fully consider the network effect, which is not dependent on external pressure, but rather relies on an individual's subjective assessment of how many relevant others are using an innovation and the benefits that result from this.

As we will show in the following sections, the application of ABM makes it possible to account for these dynamic network effects. Using the "core" TAM, an individual's intention to adopt an innovation can be

expressed as a function of PEOU and PUSE, which, in turn, depends on the "objective" attributes of the innovation (EOU, USE) and the network effect (NE):

$$int_{adopt,x,t} = f(PEOU_{x,t}, PUSE_{x,t}) = f(EOU_{i,t}, USE_{i,t}, NE_{x,t})$$

Hence, the intention of individual *x* to adopt a technology at time *t* depends on PEOU as well as PUSE at time *t* as postulated by the TAM model. The individual's perception, in turn, is determined by the ease of use (EOU) and the usefulness (USE) of the innovation *i* at time *t* as well as the sum total of all network effects for the individual at time *t*. Or, as Niederman points out: "... the rate and the enthusiasm of prior adopters influences the individual decisions to be the next adopter, thus the expected trajectory itself becomes an influence for individual adopters" (2021, p. 96).

If we assume that the "objective" characteristics of the innovation *i* do not change over time (e.g., by a product modification), then the perceptual changes of EOU and USE can be fully attributed to network effects. The left part of Fig. 3 shows the core TAM with an additional feedback loop from the actual system use back to the perceived attributes. The right part only shows the time dependence of system use and illustrates our point that, given that the objective attributes of an innovation do not exhibit temporal changes, variations in actual system use can only be attributed to the network effect. In order to fully understand a system state at time *t*, it is therefore necessary to recursively take into account the state at time *t-1* and so on. Recursion, which originates from the Latin word *recurrere* meaning "to run back," denotes a procedure or algorithm that calls itself. In our case, it is the system's current state that hinges on its state at a previous point in time. Depending on the granularity of analysis, the TAM can be thought of as a processual feedback loop (left) or an inherently recursive system (right).

5. Testing static and processual models

Theory testing is a preeminent goal of academic research and is frequently achieved by first building a model that can later be measured and validated with empirically gained data. According to our previous postulates, the question arises as to what kind of advantages would be gained from integrating dynamic aspects into such models. In order to answer this question, we first elaborate on what we deem to be the predominant methodological paradigm followed by a step-wise illustration of how processual elements can be integrated in the TAM and how ABM can help to create such processual models.

5.1. Testing static models

A widely accepted academic approach is to take an existing theory, modify it if needed, and use a cross-sectional data sample to test whether the data fit the postulated theory (Gregor & Klein, 2014). Countless methodological improvements have been made over the years, which have led to more statistically precise and sound models. The many powerful conclusions that can be drawn using techniques such as SEM notwithstanding, several limitations still exist that are more or less tacitly accepted by the research community. These include data-related distributional and reliability assumptions as well as the inability to prove cause-effect relationships or to detect non-spurious relationships (Kline, 2012; Treiblmaier, 2019). Furthermore, detecting statistically significant relationships, which is the main objective of any empirical paper in which the authors test hypotheses, depends on issues such as sample size and effect sizes, the latter of which are not always reported. Additionally, the fit indices of SEM are heuristics rather than statistical tests (L. Hu & Bentler, 1999). In spite of these shortcomings, the use of SEM for testing comprehensive multivariate models represents the current state-of-the-art of testing behavioral, attitudinal, and cognitive models. Sophisticated procedures and prescriptions have also been suggested regarding the presentation and discussion of the statistical

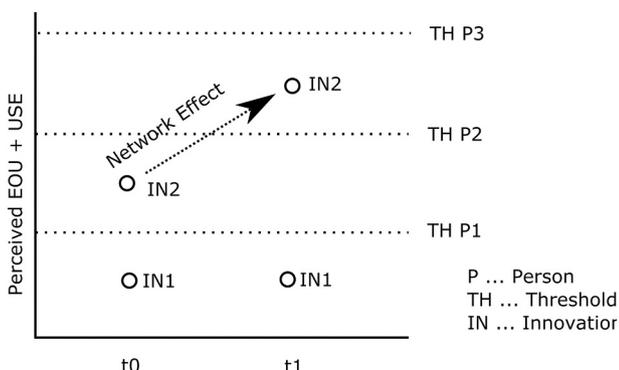


Fig. 2. Time-dependent model effects.

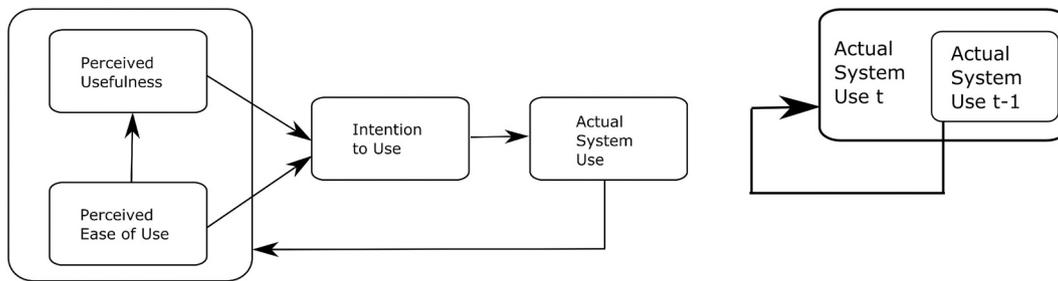


Fig. 3. A Processual and a Recursive TAM.

results (Gefen, Rigdon, & Straub, 2011; McDonald & Ho, 2002). Yet in this substantial body of existing literature, the issue of dynamically changing models has so far been largely overlooked. Thus, we propose that this prevailing methodological and theoretical paradigm needs to be enhanced to be able to fully account for the characteristics of processual models.

5.2. Testing processual models

Using ABM in combination with parameter estimates resulting from an SEM model may help to overcome some of the aforementioned limitations by providing a processual perspective that also includes a temporal component such as the network effect. Since ABM is based on programmed models, a modeling language such as UML (Unified Modeling Language) can be used to visualize the system design (see Fig. 4). Using a UML class diagram² for a seemingly simple model such as the TAM makes it clear that this model is actually a mix of methods (behavioralIntentionToAdopt(), assessEaseOfUse(), assessUsefulness()) and attributes (USE, EOU, PEOU, PUSE). A class diagram forces researchers to clearly articulate how the various attributes impact each other in order to yield a specific adoption decision. The World class is the environment in which innovations and persons coexist. In the Person class, the addition of the term “perceived” (PEOU, PUSE) makes it clear that it is the individual about which we are talking. The “objective attributes” of the innovation (EOU, USE) are related to individuals’ perceptions such that individuals reevaluate PEOU and PUSE at each step in time based on the innovation’s objective EOU and USE attributes and in

relation to their own personal network. Based on this evaluation, an individual decides whether or not to adopt. This, in turn, will influence the decisions of other individuals at a later point in time.

We have to stress that such a mix of attributes and methods is not an exclusive feature of the TAM. Rather, we argue that this is a common characteristic of many widely used models if modeled accordingly. One example is the DeLone and McLean information systems success model, wherein (perceived) system quality and service quality are attributes of the user, while the “intention to use” is modeled as a method (DeLone & McLean, 2003). Another example is the expectation confirmation theory (Oliver, 1977), in which perceived performance and satisfaction constitute attributes, but the (dis)confirmation process can be modeled by a method that demands cognitive effort from individuals. Even theories that cannot easily be mapped onto a model (e.g., contingency theory (Weill & Olson, 1989) or the resource-based view of the firm (Wernerfelt, 1984)) can be nicely separated into attributes and activities (methods), which subsequently allows for a programming-oriented view of the world. Integrating such a view helps to create new insights which, in turn, increase the utility of the current theory-testing paradigm.

One of the biggest advantages of ABM is the easy inclusion of network effects that can be modeled according to the structures in the real world. In this paper, we illustrate our reasoning using NetLogo 5.3.1, which is an agent-based programming language as well as an integrated-modeling environment (Wilensky, 1999). Fig. 5 compares an individualistic view of the world (left) in which each individual knows only their own preferences with a networked view (right) in which connections exist between individuals, such that one’s perceptions may depend on those of associates. A Barabási-Albert model was used to create a random scale-free network whose degree distribution asymptotically follows a power law (Albert & Barabasi, 2002). Such networks contain few nodes (hubs) with a relatively high number of connections and vice versa, which mirrors the situation in many real-world networks. In the simulation we tried out a varying number of agents, with a higher number of already existing links increasing the probability that new agents form links when they are added.

In order to illustrate the difference between a static and a processual approach, we first ran our model with a total of 200 individuals, using an individualistic view and simulated data. The result is shown on the left side of Fig. 6, with the numbers on the y-axis indicating the number of innovation adopters. In all following simulations, the initial values for PEOU and PUSE were arbitrarily chosen using a mean value and a normal distribution such that a certain number of individuals (but not all of them) was initially willing to adopt. This resembles a real-world situation in which an innovation is embraced by some early adopters. Not surprisingly, in case no network effects are present, individuals only adopt a technology when their subjective adoption thresholds for PEOU and PUSE lie below the “objective” levels of EOU and USE. Where no network effect is present, the adoption process always finishes after a single step, and the system remains in a static state. It is obvious that this pattern does not at all resemble the postulated adoption curve of the DOI theory.

In the middle chart of Fig. 6 we use the same configuration of EOU and USE but include the effect of linked neighbors adopting a

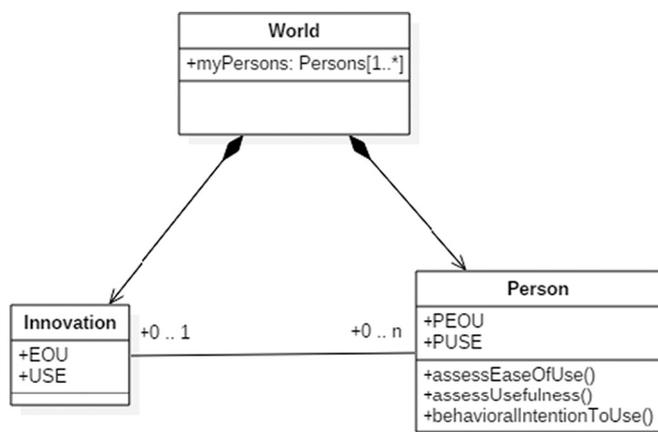


Fig. 4. Class Diagram for a Processual TAM model.

² Class diagrams in UML are widely used to model object-oriented (OO) systems. Although NetLogo is not an object-oriented programming language, UML is well suited to model the agent-oriented paradigm, which is common to any ABM programming language.

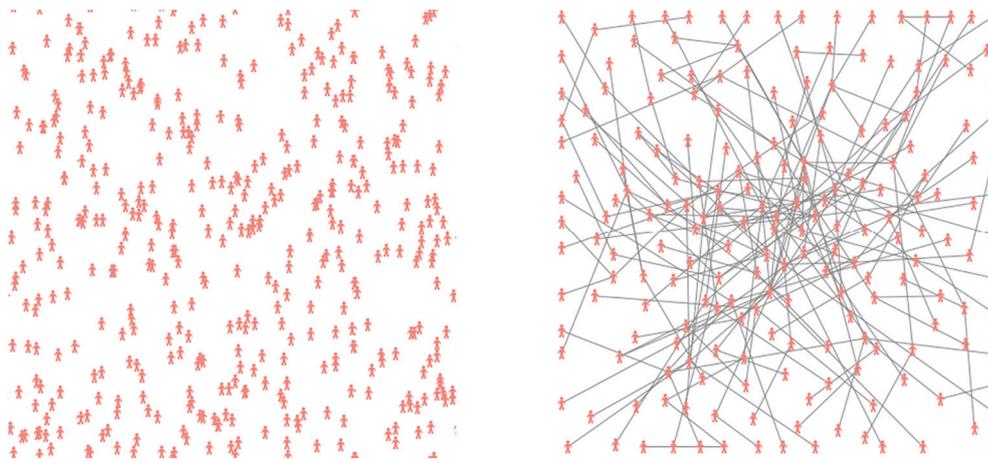


Fig. 5. An Individualistic vs. a Networked View of the World.

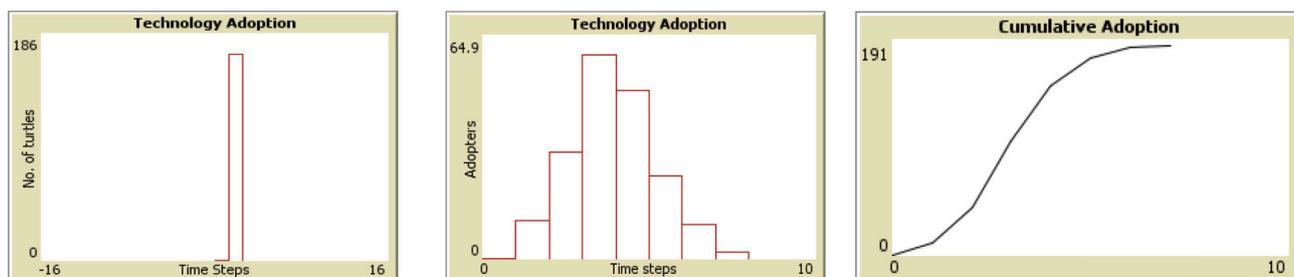


Fig. 6. Exemplary Model Results Before (left) and After (middle, right) Accounting for Processual Effects.

technology, which we presumed may impact the adoption behavior of other agents at a later point in time. This histogram exhibits the bell-shaped distribution that shows the typical sequence of innovation adoption and allows for the differentiation of early adopters, early majority, late majority, and laggards (Rogers, 2003). The number of adoptions in each step changes individuals' PEOU and PUSE, thereby causing ever more individuals to adopt. Given that neither the personal adoption thresholds of individuals nor the EOU or USE of the innovation have changed, it is the mere fact that other users who are connected in networks have adopted the innovation which convinces an increasing number of individuals to become adopters themselves. After the initial "seed" of the first round is allotted, which reaches only a small number of innovators and is represented by the first bar in the middle part of Fig. 6, the system state is determined iteratively according to its own configuration at a previous point in time (cf., also the right part of Fig. 3). Finally, on the right side of Fig. 6, the corresponding S-shaped curve of the cumulative adoption curve is shown, which now resembles the DoI adoption pattern as depicted in Fig. 1. Taken together, an ABM model is able to combine the DoI theory and the TAM, and it is capable of exhibiting time-dependent behavior based on individual configuration values of PEOU and PUSE.

So far, we have focused on the direct comparison of static and processual models, starting with a population without any initial adopters. In the next step, we investigate how a processual approach might look in a world with existing innovation users. This makes sense in all situations where an innovation already exists or when users are reconsidering their continuance intention (Li & Wang, 2017; Zhou, Fang, Vogel, Jin, & Zhang, 2012).

Fig. 7 shows three different models of a situation in which 30% of individuals initially use the technology and the different network constellations (on the left) dictate the respective adoption curves, which represent the right-hand side of the typical bell-shaped adoption distribution. Our model therefore also enables us to predict future

technology adoption given the current level of existing usage. In other words, ABM can consider the current level of adoption, which undoubtedly has a major influence on adoption rates. Fig. 7 also shows adoption rates in a market that has reached saturation and is destined to decline, independent of the features of the specific innovation.

In summary, ABM is capable of showing temporal patterns of adoption while taking into account individual behavior and attributes of potential adopters. The variables that are needed for such a simulation and how they can be gained are shown in Table 3. Although we used a fairly parsimonious model to illustrate our rationale, its additional power (as compared to models that are tested with cross-sectional data) requires more variables and assumptions as compared to traditional cross-sectional studies. This extra effort, however, leads to many insights that are not possible with existing procedures.

The results shown above are based entirely on simulated data. In order to model PEOU and PUSE, we assumed random normal distributions of these variables. The mean and the standard deviations of these constructs can easily be gained from any standardized TAM questionnaire. SEM can be used to produce estimates for these parameters in the measurement model. It is up to researchers to decide which kind of distribution they choose. They can either mimic the data that they get from a survey or instead choose an idealized distribution, such as a normal distribution, which acknowledges that the actual distribution in the population is unknown and survey data provides only an indication of how it might look. The estimates for EOU and USE are assumed values that depend on the sum total of the evaluations of all potential users in a population. Maximum likelihood estimation can be used to produce these model parameters. The number of potential adopters corresponds to the total size of the population. Depending on the hardware platform and the overall complexity of the model, populations of tens of thousands or even millions of potential adopters can easily be simulated. In case the innovation has already been adopted by a certain percentage of the population, this can also be considered in ABM (see Fig. 7). This

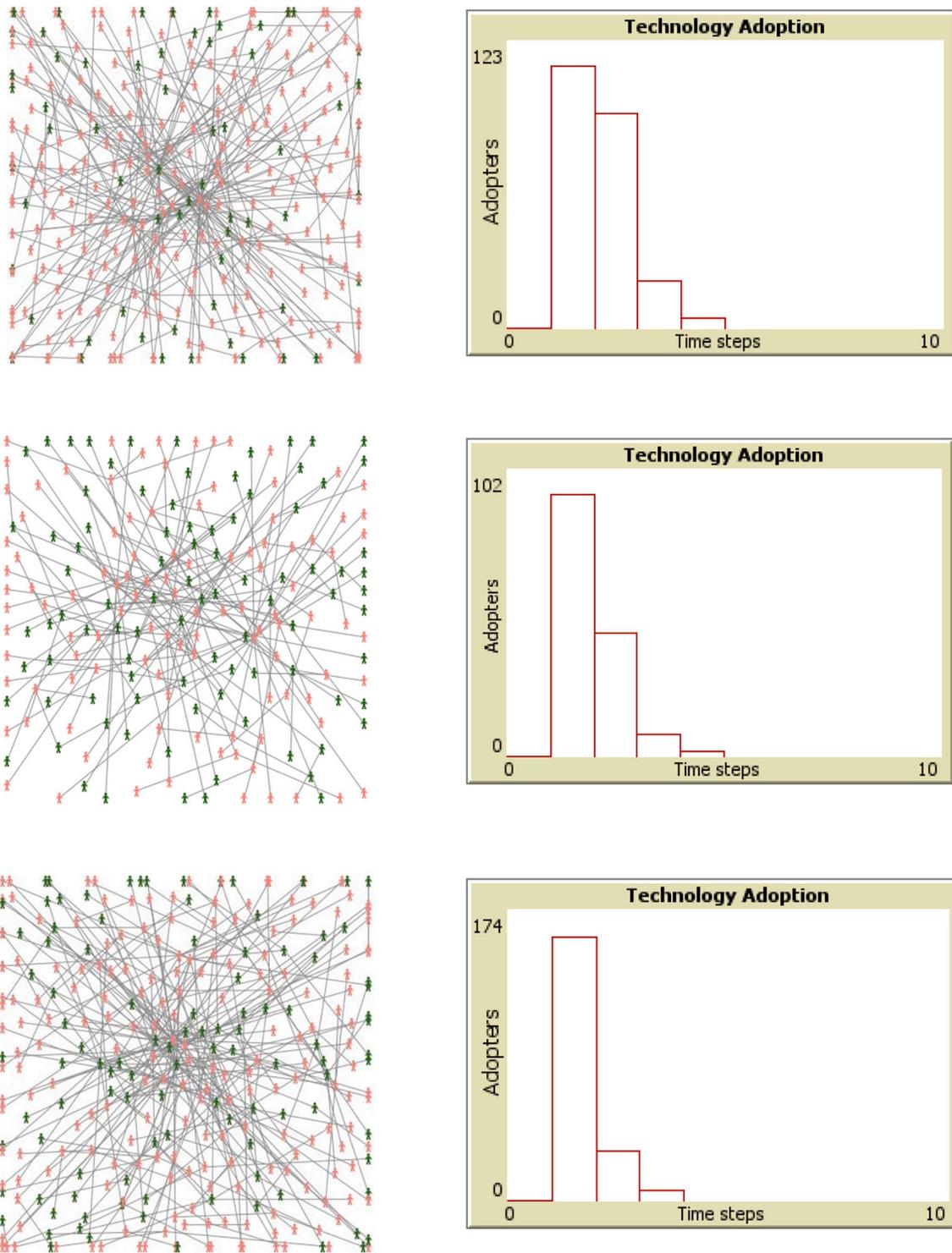


Fig. 7. Technology Adoption in a World with Existing Users.

information can also be gained from an extended TAM survey or from existing market research data. The influence of the neighbors can be estimated with multi-item scales similar to PEOU, PUSE, and BIU. The type of the network topology is up to the researchers, but survey data can be used to estimate the number of influential connections for single nodes. The core TAM model postulates an impact of PEOU on PUSE, PEOU on BIU, and PUSE on BIU, respectively. The parameter estimates from the SEM can be used to model these relationships. Finally, actual system usage can be calculated in a linear equation that measures whether a certain individual threshold has been reached. If this is the

case, the individual makes a decision to adopt. A screenshot of the interface of this model as programmed in NetLogo can be found Fig. 8 in the appendix.

Table 3 illustrates that quite a few extra data requirements may arise in cases where an ABM model is combined with SEM data. The increased power and flexibility of the new model is based on additional assumptions and variables. Several of these variables can easily be integrated into existing standardized questionnaires, and (multi-)item constructs from the literature can also be used. The main strength of this approach lies in the incorporation of real-world data, such as information about

Table 3
Data Requirements for a Processual Adoption Model.

ABM Variable	Data format	Data origin / Description
PEOU	Distribution	Multi-item construct
PUSE	Distribution	Multi-item construct
BIU	Distribution	Multi-item construct
EOU	Single value	Maximum likelihood estimation
USE	Single value	Maximum likelihood estimation
Number of potential adopters	Single value	(assessment of) population size
Number of adopters	Single value	Survey estimate, market research
Influence of neighbors	Single value	Multi-item construct
Type of network	Network topology	Choice of researchers, survey estimate, real-world data
Impact PEOU on PUSE	Single value	Parameter estimate from sem model
Impact PEOU on BIU	Single value	Parameter estimate from sem model
Impact PUSE on BIU	Single value	Parameter estimate from sem model
Actual system usage	Calculation	Calculated with abm

current adoption levels or network topologies, which makes it possible to analyze model behavior at arbitrary points in time. Furthermore, such a simulation approach allows for the testing of various dynamic scenarios without any need to gather additional data.

6. Discussion

In the preceding sections we discussed the rationale and the procedure for combining SEM and ABM and illustrated our approach using simulated data. We encourage future research to use parameter estimates from surveys as starting points for dynamic ABM models. In the following sections we first assess the applicability and advantages of our procedure from various angles and then suggest several theories that might benefit from integrating dynamic measurement procedures.

6.1. General assessment

According to the discussions above, we can now answer the five research postulates that we previously presented:

- (1) It is undisputed that the number of potential adopters in a system of limited size must change over time, independent of factors such as EOU and USE. Once a certain degree of saturation is reached, the number of new adopters will decrease dramatically, independent of the characteristics of the technology. This has been shown, for example, in the market for cellular phones, where the heyday of staggering market growth in the 1990s is long gone. Taking the current level of adoption into account helps to determine the level of market saturation without changing any attributes of the technology. The results that we got from ABM closely resemble the S-shaped curve frequently observed in empirical data. We therefore conclude that the enrichment of variance theories with processual elements helps to determine the time-dependent status of a system.
- (2) Typical adoption patterns have been recognized from empirical evidence and do not provide any justification as to why a given innovation is adopted. By integrating EOU and USE with the help of ABM, we were able to simulate different adoption patterns. If, for example, EOU and USE of a specific innovation are below the personal thresholds of the potential adopters, the innovation will fail, and, consequently, there is no adoption behavior at all. Then again, if EOU and USE exceed the PEOU and PUSE thresholds of the vast majority of potential adopters, adoption will take place immediately. It is the region in between these two extremes where the well-known S-shaped curve occurs. We therefore conclude that the combination of ABM and SEM can help to explain different adoption patterns.

- (3) Four of the main goals of theory development and application are description, explanation, prediction, and prescription. The DoI theory by itself is capable of predicting future developments in cases where the typical adoption pattern holds. However, it does not take into account those factors that are responsible for individuals' adoption decisions. The TAM model, on the other hand, makes causal claims about antecedents of adoption without being able to specify the number of adopters that will occur at a certain point in time. In this paper, we have illustrated that ABM is capable of making predictions that are based on the status of a given system. Our analysis takes into account not only the levels of EOU and USE of an innovation as well as the PEOU and PUSE thresholds of potential adopters, but also the network topology and the current adoption rate. By considering all this information simultaneously, it is possible to both predict and explain future system developments. Furthermore, the application of ABM can also be envisioned for prescriptive theories that can be helpful for the construction of an artifact (Gregor, 2006). This can be done by simulating different system states and proposing a solution that is most likely to lead to the desired result.

- (4) Common validity types in social science research include statistical conclusion validity, construct validity, internal validity, and external validity (Shadish, Cook, & Campbell, 2001). In addition to existing practices, Rand and Rust (2011) suggest four additional validation procedures that make use of real-world data and patterns. They differentiate between face validation (i.e., if the model corresponds "prima facie" to existing patterns) on a micro (i.e., individual) and macro (i.e., aggregate patterns) level. Similarly, they use empirical input and output validation to assess the quality of the input and output data, respectively. These new forms of validation expand the current repository of validation techniques of researchers when it comes to assessing the quality of their models. Using the approach we describe herein, predictions about developments in the real world can be made and real-world data can subsequently be used for model validation. Similarly, such a procedure can be tested using historical data, providing that previous system states can be calculated in order to make historical "predictions".
- (5) We find that many theories that are used in behavioral academic research include elements that render them dynamic and potentially recursive. They implicitly or explicitly include feedback loops that make the status of the system at a certain time contingent on its status at a previous time. In other words, it becomes impossible to assess the behavior and/or status of a system at a certain time without knowing its previous behavior and/or status. All of these theories potentially benefit from the inclusion of process theory and methods such as ABM in a researcher's methodological toolbox.

Based on the findings of our study, we conclude that ABM is a method that deserves further attention in academic research dealing with dynamic change due to its potential to simulate models and contribute to the testing of theory. So far, few researchers with a focus on technological transformation and digitalization have picked up ABM, but we believe that the digital business field, which is highly interdisciplinary and includes many researchers with expertise in fields such as computer science as well as economics, business administration, and other related areas, is predestined to play a leading role in combining computer simulations with more traditional social science research. Our study also supports the recommendations from Ortiz de Guinea and Webster (2017), who elaborate on the differences between variance and process approaches and suggest a toolbox for modeling that combines the best of both worlds. We conclude that ABM deserves to be part of such a toolbox.

6.2. Theoretical integration

The particular combination of the TAM and the DoI theory in this paper serves only for illustration purposes. They were chosen because of their popularity and parsimony. It is our broader intention, however, to highlight the wide applicability of our approach to a great number of theories and models that are frequently used in academic research, as shown in Table 4 in the appendix. We do not explicitly differentiate between theories that lend themselves to testing in a model and those that can be labeled as “grand theory,” the latter of which are usually more abstract. Instead, we include theories and models that we believe are “inherently dynamic” or recursive, which means that their current state might change over time even if agent-specific model parameters stay the same. Several of these theories, such as Adaptive Structuration Theory, Control Theory, Lemon Market Theory, and Organizational Learning Theory, which are described in detail by Larsen and Eargle (2015), include inherent feedback loops which make it impossible to determine a specific state of the system without knowing its previous states. Others explicitly include system states that change over time and determine how dynamic processes are executed (e.g., Absorptive Capacity Theory, Expectation Confirmation Theory, Information Processing Theory, Information Systems Success Model, TAM, and DoI theory as well as their predecessors and successors). Another group takes a broad perspective and focuses on emergent behavior and the impact of seemingly small systemic changes (e.g., Chaos Theory, General Systems Theory, Socio-Technical Theory). Finally, theories may also explicitly consider the existence of networks and their potential to shape individuals’ attitudes or behavior via interpersonal relationships (e.g., Social Network Theory).

7. Conclusion

In our study, we investigate the research question of how theory-based digital business research can incorporate temporal change. We show the importance of including processual (i.e., time-variant) effects into applied academic research and illustrate that the combination of SEM and ABM allows researchers to both explain and predict the behavior of individuals within complex and dynamic systems. This corroborates the view that, similar to variance theory, process theory is able to offer explanations and that longitudinal analyses can illuminate issues that cannot be fully addressed by relying exclusively on cross-sectional analyses (Niederman, 2021; Treiblmaier, 2017).

8. Limitations and future research

Based on the findings from this exploratory study, we underscore the importance of process theory and conclude that ABM is a useful method that can help researchers to investigate temporal phenomena from a novel angle. We do not claim that ABM constitutes a silver bullet that makes previous research obsolete. Rather, we suggest that the combination of ABM with methods such as SEM, which makes causal claims about the relationships between latent constructs, allows for richer and

more substantial theories that can be validated against real-world data. However, this comes at a price: new variables must be included that will make any model more complex, volatile, and harder to compute. This also implies that the calculated models are not deterministic and that variations of the outcomes are an integral part of the method. Additionally, the validation of such models will be more complicated since this requires the simultaneous validation of a multivariate statistical model and a temporal model, with the latter constantly changing over time.

As in any nascent field, there are plenty of opportunities for future research. Although ABM has been around for a while and sophisticated software exists, few researchers have applied it to theories that originate in the social sciences and which are frequently applied in digital business research. The applicability of ABM for exploratory and descriptive research questions, especially when it comes to complex systems with emergent phenomena, is undisputed, but the question remains as to whether it is possible to build theories by using data generated with the help of ABM. In this paper we relied mainly on the theory classification from Gregor (2006) but alternative approaches exist that extend the meaning of theory. In this regard, Sandberg and Alvesson (2021) suggest a classification consisting of five theory types (i.e., explaining, comprehending, ordering, enacting, provoking), which opens up new ways for applying the ideas presented in this paper. Specifically, ABM can be used to better understand how phenomena are produced and reproduced (i.e., enacting theory) and potentially also offers ways of creating alternative explanations (i.e., provoking theory) by simulating different scenarios.

In this paper, for the sake of simplicity, we assumed that the technology and the distribution of customer preferences did not change during the period of investigation. Further research is needed that uses sensitivity analysis to explore the implications of variable changes during the lifetime of a model and the robustness of its emerging properties to different parameter settings. ABM would indeed allow us to integrate such changes, but clearly such model modifications should be based on thorough reasoning and will add to the overall model complexity. Thus, future research needs to explore the manifold potentials of ABM in digital business research by investigating how it can help to close some of the existing methodological gaps and how it can contribute to the creation, adaptation, modification, testing, and validation of theories.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Horst Treiblmaier.

Data availability

The source code of the presented ABM model will be provided upon request.

Appendix A

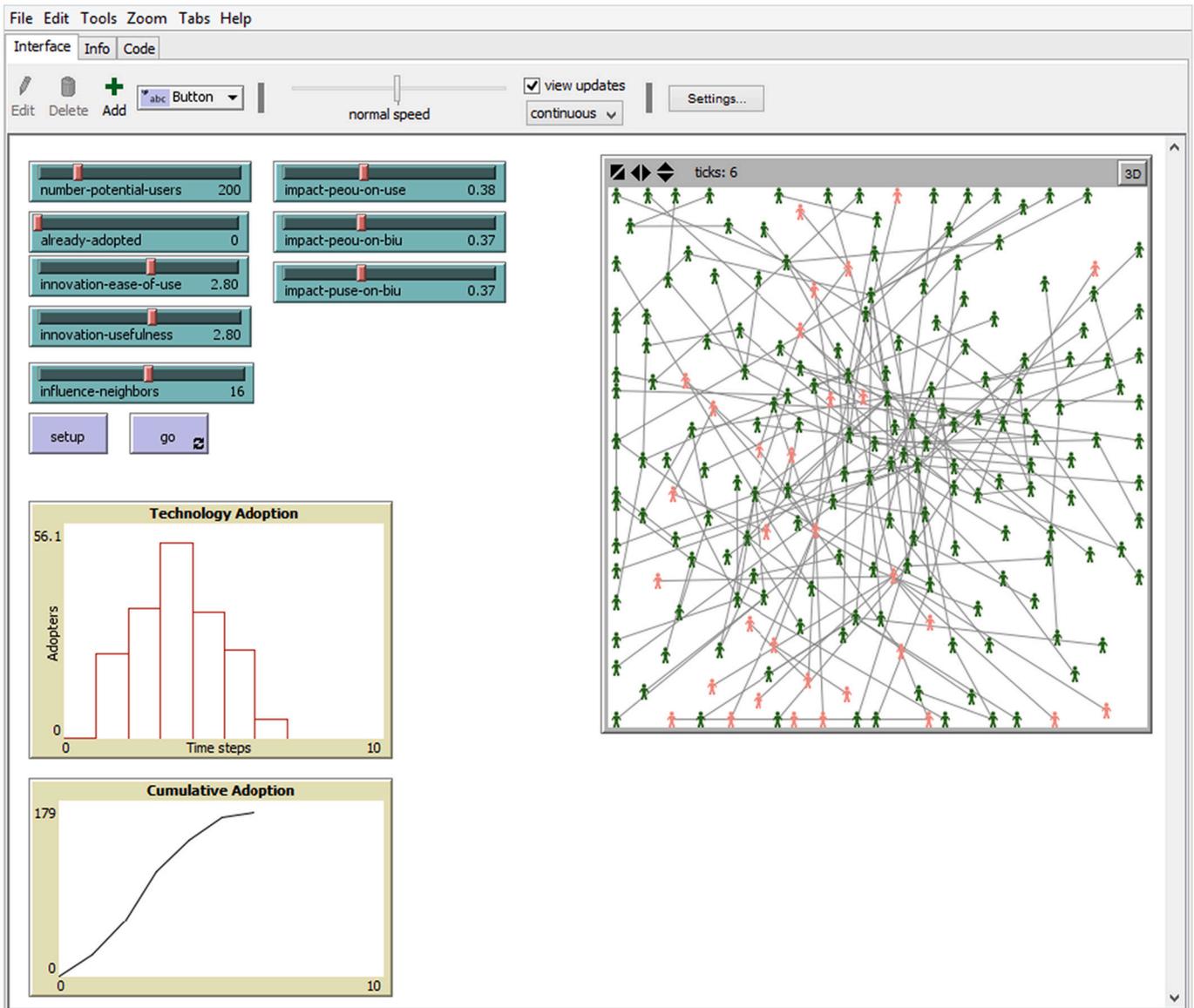


Fig. 8. Screenshot of the NetLogo Interface.

Appendix B

Table 4

Examples for Theories and Models with Processual Components.

Theory / Model	Manifestation of Effect
Absorptive Capacity Theory (Cohen & Levinthal, 1990)	A firm's capacity to identify, transform, and apply external knowledge is determined by its current level of absorptive capacity.
Adaptive Structuration Theory (DeSanctis & Poole, 1994; Giddens, 1984)	Social systems are produced and reproduced in an interactive process.
Chaos Theory (Dhillon & Ward, 2002)	The behavior of dynamic systems is highly sensitive to initial conditions.
Control Theory (Mayr, 1970)	Feedback loops lead to constantly changing states in the behavior of a system.
Expectation Confirmation Theory (Oliver, 1977)	Expectations and performance perceptions can be influenced by peers.
General Systems Theory (Bertalanffy, 1969)	Systems have organizing principles, and the elements interact with each other.
Information Processing Theory (Miller, 1956)	Information is processed, stored, and retrieved by different memories, each of which has a different capacity.
(Updated) Information Systems Success Model (DeLone & McLean, 1992, 2003)	Actual system use and network effects increase the perceived net benefits of a system, which feed back onto its antecedents.
Lemon Market Theory (Akerlof, 1970)	In case it is not possible to assess the quality of a product or service, the respective market will steadily deteriorate or disappear altogether.
Organizational Learning Theory (Daft & Weick, 1984)	

(continued on next page)

Table 4 (continued)

Theory / Model	Manifestation of Effect
Social Network Theory (Milgram, 1967)	Organizations collect and interpret data and finally take action; feedback is an integrative and ongoing part of this process. Relationships and ties within the network lead to emergent phenomena over time.
Socio-Technical Theory (Bostrom & Heinen, 1977)	Social and technical systems dynamically influence each other.
TAM Model /Theory of Reasoned Action / Theories of Planned Behavior / Diffusion of Innovations Theory, Unified Theory of Acceptance and Use of Technology (Ajzen, 1991; Davis et al., 1989; Fishbein & Ajzen, 1975; Rogers, 2003; Venkatesh et al., 2003)	Network effects depend on varying levels of existing user adoption.

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