Formalizing the Theory of Planned Behavior in Agent-Based Models, Literature review

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Abstract:

The Theory of Planned Behavior (TPB) offers a valuable framework for understanding humans decision-making. This paper explores how Agent-Based Models (ABMs) utilize TPB to investigate the interplay between social interactions, individual perceptions, and feedback from the environment in shaping behavior. We reviewed a collection of studies that utilize TPB within ABMs, focusing on how they formalize and operationalize this statistical model in a dynamic form. Our analysis reveals a diversity in approaches, which researchers implemented to handle this issue based on their research questions and available data. In most of the reviewed models, the dynamic nature emanates from evolution of SN or ATT. To account for social influence of agents and internal dynamics of the ATT or SN, researchers used Relative Agreement Model of opinion dynamics. Additionally, the review highlights various methods for translating intention into behavior within ABMs, ranging from threshold-based approaches to regression-based model. We conclude by proposing future directions for research, including incorporating dynamic updates for TPB constructs and exploring the Decomposed Theory of Planned Behavior. By addressing these considerations, researchers can develop more powerful ABMs for understanding complex social dynamics and decision-making processes.

Keywords: Agent-Based Modeling, Theory of Planned Behavior, Social Influence, Relative Agreement Model

1. Introduction

Agent-based modeling (ABM) has emerged as a powerful paradigm for modeling complex phenomena. This approach leverages autonomous, interacting entities termed “agents” each representing individual decision-making units within a defined environment (Macal and North, 2014). A core strength of agent-based modeling lies in its ability to elucidate the emergence of complex system-level phenomena from the interplay of individual agent behaviors and feedback processes (Kelly et al., 2013). This is why ABM is referred to as a bottom-up modeling approach. A dominant research focus lies in the examination of individual human beings as autonomous entities and the intricate processes that govern their decision-making (Castilla-Rho et al., 2015; Holtz and Pahl-Wostl, 2012; Kaufmann et al., 2009; Kniveton et al., 2012; Muelder and Filatova, 2018; Reeves and Zellner, 2010; Sopha et al., 2013). Social models are increasingly being coupled with diverse scientific fields, including technology diffusion (Schwarz and Ernst, 2009; Sopha et al., 2013), environmental and hydrological science (Granco et al., 2019; Kasargodu Anebagilu et al., 2021; Noeldeke et al., 2022; Pouladi et al., 2019) , energy (Muelder and Filatova, 2018; Rai and Robinson, 2015), psychology (Richetin et al., 2010), health and safety (Verwaart and Valeeva, 2011; Wang and Hu, 2012). This interdisciplinary approach facilitates the exploration and illustration of feedback loops between human entities and their real-world physical environment.

While rooted in economics, traditional behavioral models like Rational Choice Theory (Simon, 1978) often rely on unrealistic decision-making assumptions. These assumptions, including self-interested utility maximization, perfect knowledge, and unlimited cognitive capacity, can lead to inaccurate portrayals of agent behavior within simulations and potentially generate unrealistic outcomes when compared to real-world phenomena (Constantino et al., 2021; Noeldeke et al., 2022; Pouladi et al., 2019; Schlüter et al., 2017). Economic models prioritize economic factors in decision-making (Faber et al., 2010; Günther et al., 2011; Sorda et al., 2013), while cognitive agent models move beyond mere economic factors, explicitly representing the dynamic interplay of cognitive and psychological influences within social interactions (Zhang and Vorobeychik, 2019).

Psychological theories play a particularly significant role in shaping the decision-making rules that govern agent behavior within ABMs. The Theory of Planned Behavior (TPB) proposed by Ajzen (1991) has emerged as a prominent framework within the agent-based literature on human decision-making (Constantino et al., 2021; Githinji et al., 2023; Groeneveld et al., 2017; Schlüter et al., 2017). The TPB extends the understanding of human decision-making beyond bounded rationality by incorporating the influence of socio-psychological factors. It posits that attitudes, subjective norms, and perceived behavioral control interact to determine an individual's behavioral intentions (Githinji et al., 2023). Attitude refers to an individual's evaluation of a behavior, considering it favorable or unfavorable. Subjective norm reflects the perceived social pressure to perform a behavior. Finally, perceived behavioral control captures the perceived ease or difficulty of performing the behavior, influenced by past experiences and anticipated obstacles (Ajzen, 1991; Fishbein and Ajzen, 2011). Leveraging well-established theories in ABMs offers multiple advantages. Firstly, a theory-based approach facilitates reuse and comparison of models by providing a common ground. Additionally, using theories for modeling decision-making in ABM reduce the numerous options of inclusions in decision-making models (Schwarz et al., 2020).

While utilizing psychological theories such as TPB in ABMs offers advantages, modelers face the challenge of translating these abstract concepts into concrete code. This process, known as operationalization, requires creativity to transform psychological notions into specific model elements (Muelder and Filatova, 2018; Schwarz et al., 2020). ABMs excel at simulating the dynamic interplay of behaviors and interactions over time. However, TPB was primarily designed to identify static, causal relationships within populations, offering a statistical snapshot rather than a framework for individual behavior change. Consequently, translating statistical model into decision-making rules for heterogeneous agents within an ABM is a burden that modeler deal with. This paper conducts a critical review of few existing literature, exploring how researchers have integrated the TPB within ABMs with a specific focus on innovation diffusion and socio-environmental systems. While TPB offers valuable insights into human decision-making, its static nature presents a challenge for capturing the dynamic behavioral evolution inherent in ABMs. We examine how researchers have bridged this gap in various contexts.

2. Review of application of TPB in ABMs

Statistical analysis, particularly regression techniques, plays a critical role before applying the TPB within an ABM. This analysis helps assess TPB's explanatory power for the target behavior and determines the weights of each TPB determinant on intention. These weights are then crucial for translating TPB into decision-making rules for agents within the ABM (Scalco et al., 2018). However, the process of formalizing these theoretical statistical models to computational dynamic models may unveil inherent barriers (Schlüter et al., 2017). Scalco et al. (2018) addressed the growing need to integrate psychological theory into ABM. The authors initiated first steps to bridge the gap between psychology and computer science by advocating for the TPB as a tool to enhance the behavioral realism of in ABMs. Moreover, Muelder and Filatova (2018) illustrated that the inherent subjectivity and interpretability of social concepts allows modelers to operationalize them in diverse ways within their models and codes. The study investigated how variations in implementing the TPB structure within an ABM can influence the simulated adoption rate of solar panels in a single case study. This finding highlights the sensitivity of ABM outcomes to the specific operationalization of social science theories. Hence, by examining how researchers across disciplines have operationalized the TPB within ABMs, this review aims to identify transferable insights and best practices. This analysis can provide valuable general guidelines for modeling TPB's core components – attitude (ATT), perceived behavioral control (PBC), and subjective norms (SN) – as well as the transition from intention to behavior within ABM simulations.

Kaufmann et al. (2009) investigated the spread of organic farming practices among farmers in two European Union member states, Latvia and Estonia. Their goal was to understand the factors influencing farmers' decisions to adopt organic methods. Limited and inconsistent adoption of certified organic farming practices necessitates a deeper understanding of the decision-making factors influencing farmer conversion. This knowledge is crucial for designing effective policy interventions, such as financial incentives and farm support mechanisms, to promote widespread organic farming adoption. The model was applied to regions with a high concentration of organic farms. Data from surveys informed the model's parameters. Study employed different methods to derive weights for factors influencing organic farming adoption among non-adopters and adopters. Linear regression was used to analyze data on revealed intention, ATT, SN, and PBC from non-adopters. For adopters, weights were based on profitability measures and agri-environmental satisfaction index as dependent variables. To consider the heterogeneity of agents in the model, farmers were categorized into distinct groups using hierarchical cluster analysis. This categorization was based on factors such as ATT, SN, PBC, and associated levels of uncertainty. Through this process, clusters exhibited relative homogeneity within themselves while demonstrating heterogeneity between them. The determination of the number of clusters for each case was conducted manually to ensure a realistic representation of the data. Subsequently, farmers within each cluster were distributed according to a normal distribution, utilizing the mean and standard deviation specific to their respective clusters. The social network of agents mirrored a "small world" network characterized by a left-skewed degree distribution. Most farmers had a limited number of connections, while a select few had extensive connections. Following the TPB survey (Ajzen, 1985), Kaufman et al. (2009) characterized each agent with three attributes: ATT, SN, and PBC. These attributes ranged from -1 (highly negative) to +1 (highly positive) and represented the agent's internal state regarding adoption of organic farming practices. The model further incorporated weights to account for the relative importance of each attribute in shaping the agent's overall intention. The study also explored social influence within the ABM, drawing inspiration from the relative agreement model proposed by Deffuant (2002). Their model simulated social influence occurring between interconnected agents in a random order during each time step. The model conceptualized an agent's opinion (intention) and another agent's subjective norm as segments on a line. If their segments overlap, agent i has the capacity to influence agent j, thereby aligning agent j's subjective norm more closely with agent i's opinion. Researchers defined an adoption threshold to categorize agents as adopters. Agents with intention exceeding this threshold were classified as adopters. Notably, the threshold itself was derived empirically by averaging the intention of non-adopters who expressed future adoption intent in the survey, but the model was not validated with empirical data. The study examined the impact of external factors on adoption within their model. They explored how increased subsidies and stronger support from organic farm advisors influenced adoption rates. The authors assumed that a subsidy or higher market demand would increase farmers' perceived ability to apply organic farming practices successfully, so they increased conventional farmers' PBC. Moreover, the effects of the advisor were modeled through having a positive influence and an increase in the PBC and SN of the farmers who were advised. This analysis provided insights into how social dynamics and adoption patterns respond to external forces. Their model revealed that economic factors, particularly subsidies, played a more significant role in driving organic farming adoption compared to social influence alone. However, the study also found that the combination of social influence and economic incentives resulted in the highest adoption rates.

In another study, Schwarz and Ernst, (2009) argued that traditional modeling approaches often struggle to capture the complex social dynamics that influence how people adopt new environmental friendly technologies such, such as showerheads, toilet flushes, and rain-harvesting systems, among Southern German households. ABM, with its ability to simulate individual decision-making and social interactions, offers a valuable tool to address this gap. The authors ground their model in empirical data on water-saving technologies, making the model more applicable to real-world scenarios. To gather empirical data, they employed a mixed-methods approach including written questionnaire and a small telephone interview. The questionnaire was built upon the TPB, which explores the factors influencing behavioral intention and adoption. In addition to TPB factors, the researchers incorporated aspects of innovation characteristics to further understand how these features influence ATT and PBC. They analyzed the survey data using statistical techniques like structural equation modeling and linear regressions. This allowed them to identify the relative importance of different decision factors for adopting water-saving technologies within specific lifestyle groups and for different innovations. To categorize adopters, they used the concept of Sinus-Milieus® – one of the leading lifestyles approaches in marketing in Europe, and agents were clustered into five groups of lifestyles, Postmaterialists, Social Leaders, Traditionals, Mainstream, Hedonistic milieus. The researchers leveraged a modified version of the Watts and Strogatz Small-World algorithm (1998) to generate the social network within their ABM. It was modified to include both spatial proximity and affinity to other lifestyles. The model incorporates different decision-making processes for distinct agent types based on their lifestyle category. Postmaterialists and Social Leaders agents use a more complex, deliberate decision-making process informed by the TPB. In their study, the ATT is function of environmental performance, ease of use, saving of costs, compatibility with existing infrastructure, PBC is function of compatibility with infrastructure and installation costs, and SN is function of percentage of installation in agent's network. On the other hand, Traditional, Mainstream, and Hedonistic Milieus agents use a simpler decision heuristic. They either choose the technology with the seemingly best attributes ("take-the-best") or imitate the choices of their peers. SN update based on the adopter in agents' social network. They validated their model through period of 1980 to 2005. The researchers explored the impact of different policies and social trends on the diffusion of water-saving technologies within their ABM from 2006 to 2020. The analysis included a baseline scenario, a scenario simulating increased public environmental awareness (Information Campaigns) by increasing importance of environmental issues in the model, a scenario investigating the impact of financial incentives for water-saving technology (Subsidy) by increasing water-saving parameter in the model, and lastly, a scenario modeling the effects of implementing regulations.

In another research, Kniveton et al. (2011, 2012) presented a novel approach to studying future migration patterns in Burkina Faso. The research critiques traditional methods for predicting climate-induced migration, arguing they lack sophistication in capturing individual decision-making processes. The authors proposed an agent-based modeling framework informed by the TPB. This framework allows for the simulation of migration decisions based on individual characteristics and environmental stimuli. The study utilized the Enquete Migration, Insertion Urbaine et Environnement au Burkina Faso (EMIUB) to inform the ABM. The study employed survey data to classify agents into five distinct geographic locations within Burkina Faso. Furthermore, within each location, agent differentiation was implemented based on demographic characteristics such as gender, age, and marital status. Besides demographic characteristics, origin zone, and current rainfall patterns utilized to determine the probability values of attitude towards migration. Higher probabilities signify a stronger positive attitude towards each migration option. In the study, the PBC component of migration decisions was based on two variables: experience of migration and assets. Initially, the experience rate of each agent was directly obtained from the EMIUB data when the model was initiated. However, this experience rate could also be updated throughout the simulation by engaging in migration. Agents with greater assets and more migration experience were more likely to perceive themselves as capable of undertaking migration. As agents accumulated assets and gained experience with migration over time, their confidence in their ability to migrate increased, influencing their decision-making process. In the ABM used in the study, the SN was determined based on analysis of the EMIUB dataset. This aspect of the conceptual model focuses on how agents interact with each other and how an individual's peers can influence their migration decisions. At the beginning of the model, each agent is connected to fifty others through a small-world network (Kniveton et al., 2012). These networked agents exchange messages, sharing their most recent migration decisions with each other. Based on the messages received, an agent calculates peer opinion values for each migration option they are considering. This process allows agents to take into account the collective influence of their peers when making their migration decisions. Intention of agents were the adaptive decision-making processes facing climate change, specifically focusing on seasonal migration as an adaptation strategy. The research investigated how agents selected among five migration options, relocation to one of four different internal zones in Burkina Faso or international migration, in response to climate change. Each agent evaluated these options based on a combination of three factors. It is function of ATT, PBC and SN. I = ATT*PBC*SN. Each agent assigns a score to each available migration option. Following the computation of behavioral intention scores, the agents evaluate the available options, including remaining in their current location or migrating to one of the alternative destinations. If agent's maximum score is to migrate, PBC should be > 0 until agent could materialize it. The model was validated and demonstrated a strong correlation between the simulated migration flows and real-world observations from the EMIUB survey for the 1970-2000 period. Building on the model's successful replication of historical migration patterns, the study explored four future scenarios for Burkina Faso extending to 2060. These scenarios incorporated a multifaceted approach, considering how various factors might interact and influence migration trends. The model simulations revealed contrasting migration patterns under different climate scenarios (Kniveton et al., 2012). When simulating a future climate with increased precipitation, the model predicted a decrease in migration compared to what would be expected under current climate conditions. Conversely, a scenario with a drier climate only indicated brief periods of marginally higher migration compared to the present climate (Kniveton et al., 2012).

Sopha et al. (2013) examined the adoption and diffusion of heating systems in Norway. In order to test the variables identified from literature that could determine the adoption of wood-pellet heating systems, the researchers conducted a survey. The survey also provided input parameters for the ABM simulation. They employed a clustering technique to segment households into a manageable number of distinct lifestyle groups. These groups would ideally share similar consumption patterns. The study employed income level and basic values as proxies for lifestyle, with the aim of understanding how lifestyle influences attitudes towards a particular technology. Through a cluster analysis, they identified three distinct household groups: Low-medium income and post-materialism values, Medium-high income and medium materialism values, Low-medium income and materialism values. Furthermore, the study employed a small-world network configuration to represent the social network within their ABM. This selection was informed by a prior sensitivity analysis that investigated the influence of various network structures on the diffusion rate of heat pumps. To capture the hallmarks of a small-world effect, the model established a two-fold approach for household interactions. First, households interacted with their geographically proximate neighbors based on a pre-defined "radius," reflecting the influence of local social interactions. Second, the model incorporated random interactions with the remaining population. This latter element introduced the "small-world" characteristic, enabling long-distance connections that could bridge geographically isolated groups and potentially accelerate the diffusion of the technology. Researchers implemented a sophisticated decision-making process within their agent-based model, reflecting the nuances captured in their empirical survey. The model implemented decision strategy following the meta-theory of consumer behavior, which was specifically designed for simulating consumer choice (Jager, 2000). 23.5% of modeled households exhibited repetition, habitually sticking with their current electric heating system. Alternatively, 59.1% acted as deliberation, engaging in a rational evaluation of all three heating options (electric, air-to-air heat pump, and wood pellet). This evaluation, grounded in the TPB, ultimately led them to select the system with the highest perceived value proposition. Imitation also played a role, with a small possibility (2.1%) that a household would adopt the heating system most prevalent within their social network. Finally, social comparison (15.3%) could occur, where households were not solely focused on their existing system but rather weighed it against the most popular option among their peers, ultimately selecting the one perceived as superior based on this social comparison. Selecting the better alternative is based on TPB. This incorporation of various decision-making strategies, ensured the model reflected the diverse ways homeowners might approach choosing a heating system, moving beyond a one-size-fits-all approach. For households employing the TPB, the selection of a heating system hinged on a weighted function of ATT, PBC, SN. Each construct was calculated for all three heating options. For each heating option ATT and PBC are function of fuel price stability, indoor air quality, functional reliability, total cost, required work. Also, SN is a function of the number of peers a household communicates with about heating systems and the network configuration. The model incorporated a mechanism to translate an agent's decision to adopt a new heating system into a concrete action. This involved converting the decision choice into a specific installation rate. To ensure the robustness of their ABM, they implemented a validation strategy that relied on independent data. This data was not used for calibrating the model but served solely for validation purposes. Simulations were run toward understanding the effect of various policy interventions on diffusion patterns of heating systems as well. Simulation results suggest that increased adoption of wood-pellet heating is dependent on improved both functional reliability and fuel stability.

Rai and Robinson (2015) acknowledged limitations in ABM for studying technology adoption, particularly the use of oversimplified behavioral rules. To address shortcomings, they proposed a more robust approach – a theoretically-grounded and empirically-driven ABM specifically focused on residential solar photovoltaic (PV) adoption. To strengthen their ABM of residential solar PV adoption, Rai and Robinson (2015) conducted a longitudinal survey of PV adopters in Austin, Texas. The survey spanned three waves from 2011 to 2014. Based on the attitudes of the initial adopters, they develop a spatial statistical model to calculate general public attitude. ATT is modeled as a function of home parcel size, ratio of tree-cover to size, and home value per unit size, and attitudinal heterogeneity associated with geographical location. Recognizing that social interactions influence technology adoption, the study integrated an opinion dynamics model into their ABM. For each ATT towards PV household has an "uncertainty" level. The initial level of uncertainty (U) was inversely proportional to the absolute value of the initial ATT. This reflects suggesting that individuals holding moderate views are more receptive to new information, leading to greater initial uncertainty. Based on relative agreement model (Deffuant, 2002), the extent to which agent i's attitude influenced agent j was contingent upon the overlap (agreement) between their existing attitudes. Furthermore, the social network within the ABM adopted a "small-world" structure. At each time step, each agent interacted with a predetermined number of randomly chosen agents from their social network. This network structure prioritized connections with geographically proximate and economically similar agents. This design decision reflects the influence of local communities and shared socioeconomic backgrounds on social influence processes. After updating attitudes of the agents based on their interaction it was compared to a global threshold. Also, PBC regarding ability to afford solar are compared to current payback periods (PP). PBC, a static attribute, captured a household's initial assessment of their suitability for solar PV based on a one-time calculation using home value and physical features like size, tree cover, and irradiance. In contrast, PP was a dynamic variable recalculated at each time step. It considered as a function of the value of the electricity produced by the solar system, the per unit price of the solar system, utility rebates, and the federal investment tax credit for each time period, and the annual system electricity generation. This dynamic approach recognized that the financial viability of solar PV can fluctuate over time due to evolving economic factors. They incorporated clear decision criteria within their ABM for residential solar PV adoption. For an agent to adopt solar PV, both their ATT and PBC had to surpass respective thresholds. Rai and Robinson (2015) ensured their ABM of residential solar PV adoption reflected real-world dynamics through a meticulous calibration process. The simulated cumulative number of solar installations over time was compared to the actual data from Austin. This fitting process ensured the model's behavior mirrored real-world adoption patterns, strengthening the model's credibility and generalizability. The researchers then harnessed the ABM's capabilities as a "virtual laboratory" to explore the potential of policy interventions. The first policy scenario simulated a program specifically targeted at low-income households. This simulation yielded valuable insights, suggesting that substantial increases in rebate levels would likely be required to achieve a significant positive impact on solar PV adoption within this demographic group. Secondly, the researchers investigated the influence of rebate levels across the entire population. Their findings indicated a dynamic relationship between rebate adjustments and adoption rates. Early in the simulated timeframe, when the existing installed base of solar PV systems was low, changes in rebate levels had a relatively modest impact on adoption. However, as the simulation progressed and the installed base grew, the impact of rebate adjustments became progressively more pronounced. This amplifying effect can be attributed to the social influence mechanisms embedded within the ABM's social network structure.

In another study, Pouladi et al. (2019) presented a novel agent-based socio-hydrological modeling approach for the restoration of Urmia Lake. Integrating ABM with the TPB, the model simulates farmer decision-making regarding water use in the Zarrineh River Basin. By incorporating social factors influencing agricultural water use behavior, the model offers a more comprehensive understanding of the human-water relationship in the Urmia Lake basin. The study employed a survey approach, interviewing and administering questionnaires to 274 farmers in the Zarrineh River Basin. To analyze the relationships between ATT, PBC, and SN with intentions of farmers regarding choosing water use behavior, selecting less water demanded crops or intense water demanded crops, the authors utilized path analysis, a statistical technique that examines the causal relationships between variables in a model. They employed a multi-tiered classification approach to distinguish farmer agents based on three key characteristics: age, education level, and farmland size. This research utilized a three-step decision-making process within its ABM to simulate historical crop selection behavior by farmers in the Zarrineh River Basin. This process integrated both economic considerations and environmental awareness. First, the ABM prioritized financial security for farmer agents by comparing their projected twelve-month savings with the established poverty threshold for the year. If savings fell below this threshold, agents prioritized maximizing profit during crop selection, potentially compromising water-conserving practices. Second, the ABM incorporated farmer recollections of past precipitation patterns. When an agent recalled a wet year, it prioritized profitability similar to Step 1, potentially leading to increased water usage. Conversely, if farmers perceived a drought year but their savings exceed the poverty threshold, they proceeded to Step 3. In the last step of decision-making, where the agents should decide about the conservation of water resources, their intention and behavior will be determined through the TPB. Behavior is a function of intention and PBC. Based on a statistical equation, and amount of ATT and PBC from ABM, agents who have reached to the third step of decision making tree, choose their crop types. This multi-layered approach acknowledged the complex interplay between economic necessities, past experiences with water availability, and environmental awareness in influencing historical farmer decision-making. The research identified income as a significant factor influencing both ATT and PBC. Consequently, the ABM incorporated variations in financial conditions throughout the modeling process. Each agent type's ATT and PBC values were dynamically adjusted based on a comparison of current profits with the previous year's profits. If the comparison indicated a decline in financial well-being, the ATT and PBC values for that agent were lowered in the subsequent agricultural year. Conversely, improved financial conditions led to increased ATT and PBC values. In cases where financial conditions remained unchanged, the ATT and PBC values were maintained. However, the mechanism that their ATT and PBC changes was not explicitly determined. Within the defined psychological parameters of the ABM, only the subjective norm was assumed to remain constant throughout the study period (2009-2017). The authors validated their coupled socio-hydrological model by comparing the simulated discharge of the Zarrineh River into Urmia Lake with historical data. The model achieved a Nash-Sutcliffe efficiency of 0.92, indicating a strong correspondence between the simulated and observed discharge values. Analysis of the model's results revealed that financial conditions, farmland size, farmer age, and education level were all significant factors influencing farmer decision-making. Notably, financial constraints played a crucial role. Small-landholding farmer agents, identified by the model as having savings below the poverty threshold, primarily selected crops like sugar beet and alfalfa, potentially due to their higher revenue. Furthermore, the authors compared the performance of their TPB-based model with an economic model assuming purely rational agents. This comparison revealed that incorporating the TPB framework into the agent-based model led to a more accurate simulation of farmer conservation behavior because NSE of the coupled socio-hydrological model decreased to 0.8 in the economic model. This finding suggests the importance of social and psychological factors alongside economic considerations.

3. Discussion

The integration of the TPB within ABMs represents a promising approach to understanding and simulating complex human decision-making processes across diverse domains and policy evaluations even though there are challenges in translating statistical models to dynamic form. Through a comprehensive review of several studies applying TPB within ABMs, we gain insights into the methodologies, model structures, findings, and policy implications of this interdisciplinary research endeavor. The methodological approaches employed across the studies showcase the diversity of techniques used to integrate TPB into ABMs. From data collection through surveys to statistical analyses and model implementations, researchers demonstrate a rigorous approach to model development and validation. By validating their models against real-world data, researchers enhance the credibility and robustness of their findings, thereby strengthening the utility of ABMs as decision support tools for policymakers and stakeholders. Furthermore, the policy implications derived from these studies underscore the practical relevance of ABMs informed by TPB. By simulating various intervention strategies and policy scenarios, researchers are able to assess the potential impact of different approaches on behavior change and system dynamics. From targeted financial incentives to information campaigns and regulatory measures, ABMs offer valuable insights into the effectiveness of policy interventions in promoting desirable outcomes, such as sustainable resource use and technology adoption.

The reviewed studies illustrate diverse and effective applications of TPB in ABMs. Drawing upon the reviewed literature, excluding Kniveton et al. (2011, 2012), we identify all other studies (Kaufmann et al., 2009; Pouladi et al., 2019; Rai and Robinson, 2015; Schwarz and Ernst, 2009; Sopha et al., 2013) developed a survey based on TPB with their specific research question. This survey approach facilitated the establishment of regression models to explore the causal relationships between TPB constructs and behavioral intention. This step is crucial for parametrizing (Smajgl et al., 2011) the ABM. The weights derived from this statistical analysis were then used to initialize the ABM, effectively translating psychological theory into actionable decision-making rules for the agents.

To create a representative artificial society within the ABM, majority of studies utilized statistical methods such as clustering for categorization of the agents. Categorization fosters the creation of manageable social groups that retain sufficient heterogeneity to capture the essential characteristics of the population (Kaufman et al., 2009). Another reason that modelers decide to categorize the ABM is for up-scaling. As the survey results are based on limited data, in such cases, it can be difficult to directly translate survey findings into a representative large-scale ABM population. Categorization allows researchers to overcome this limitation by creating manageable social groups based on survey features and variables. Within each category, agents can be proportionally distributed and further diversified through the introduction of stochastic variations. This approach enables the construction of an artificial society with sufficient heterogeneity, even when survey data is limited. The specific features employed for agent clustering vary across studies, reflecting the research question and the available data (Kaufman et al., 2009; Pouladi et al., 2019; Rai & Robinson, 2015; Schwarz & Ernst, 2009; Sopha et al., 2013). The selection of features for agent clustering hinges on the characteristics of the survey data. If the data lacks significant variation, chosen clustering methods might not yield a sufficient number of distinct groups that meet the desired balance of homogeneity within and heterogeneity between clusters. In such cases, researchers may need to explore alternative features or refine their clustering approach to ensure effective representation of the social environment within the ABM. The reviewed studies highlight two prevalent categories of clustering features: socio-psychological factors (attitude, perceived behavioral control, subjective norm, values) employed in studies on technology adoption (Kaufman et al., 2009; Schwarz & Ernst, 2009; Sopha et al., 2013) and demographic factors (age, education, farm size, income, gender) used in migration or socio-environmental research (Pouladi et al., 2019; Kniveton et al., 2011, 2012).

The other important issue in initialization artificial societies is capturing the real-world social networks. In reviewed papers, studies utilized small-world networks to address this challenge in their ABMs (Kaufmann et al., 2009; Kniveton et al., 2012; Rai and Robinson, 2015; Schwarz and Ernst, 2009; Sopha et al., 2013). These networks are characterized by high clustering, where agents connect with similar others, and short path lengths, enabling efficient information flow and interaction across the network. This reflects real-world social systems where individuals interact with close neighbors but are also influenced by broader trends. However, the operationalization differed across studies. Kaufmann et al. (2009) leveraged real-world social network data to construct a small-world network with a left-skewed degree distribution, reflecting the observed tendency of organic farmers to connect more with each other. In contrast, Schwarz and Ernst (2009) employed the revised Watts and Strogatz algorithm (1998) to generate an artificial social network with small-world properties, considering both spatial proximity and lifestyle affinity. Sopha et al. (2013) selected a small-world network configuration in which agents interact with neighbors based on spatial proximity acquired by using a “radius” and interacts with the rest of the population randomly. Rai and Robinson (2015) placed agents in small-world networks where connections were primarily based on geographic proximity and economic similarity. These diverse approaches highlight the flexibility of small-world networks in representing social influence within ABMs.

Social interactions are significantly impacted by the phenomenon of social influence. During these interactions, individuals may exhibit a shift in their opinions, attitudes, beliefs, or behaviors to achieve greater alignment with those they encounter. This convergence often stems from a perceived validity in the arguments presented by others (Flache et al., 2017; Myers, 1982). A highly influential work in this area is the Relative Agreement Model, introduced by (Deffuant, 2002). Our review identified a limited application of the Relative Agreement Model (RAM) within the examined studies. Only two out of eight studies Kaufmann et al. (2009) and Rai and Robinson (2015) utilized RAM to explore how social interactions shaped agent internal dispositions which lead to change their behaviors. Kaufmann’s (2009) work on organic farming adoption demonstrates how RAM can influence an agent’s (j) perception of subjective norm based on the similarity with another agent’s (i) intention. Similarly, Rai and Robinson (2015) employed RAM in their solar PV adoption model, where the extent of influence depended on the alignment of agents’ attitudes. This finding highlights the potential of RAM for capturing social influence in ABMs. However, it also raises questions about the generalizability of RAM and social influence models for other researchers’ specific research questions.

An essential aspect of utilizing the TPB in ABM involves how researchers operationalize its various constructs, including ATT, PBC, and SN. Kaufmann et al. (2009) proposed a norm-based model where agents update their SN, uncertainty, and intention due to opinions of other farmers. The model leverages the Relative Agreement Model to govern how social interactions shape SN. Other studies incorporating SN in their TPB models treated it as a fraction of peers in social networks who adhere to a common norm, such as the fraction of agents adopting a specific technology (Schwarz and Ernst, 2009; Sopha et al., 2013). Similarly, in various studies, ATT and PBC were functions of other parameters, although these parameters were often static. For example, Schwarz and Ernst (2009) modeled ATT as a function of environmental performance, ease of use, cost savings, and compatibility with existing infrastructure, while PBC was influenced by factors like compatibility with infrastructure and installation costs. Sopha et al. (2013) considered factors such as fuel price stability, indoor air quality, functional reliability, total cost, and required work to model ATT and PBC. In Rai (2015), ATT was influenced by home parcel size, ratio of tree-cover to size, home value per unit size, and geographical location, while PBC was modeled based on agents' financial resources and relevant physical features of their homes. In other studies, focusing on socio-environmental systems, ATT and PBC were influenced by net benefit (Pouladi et al., 2019), and in Kniveton et al. (2011, 2012) PBC was influenced by experience and assets. Overall, these studies demonstrate the flexibility of ABMs in capturing the interplay between ATT, PBC, SN, and social influence within the TPB framework. The specific implementation of these factors varied based on the research question and the complexity of the decision-making process being modeled. In general, modeling ATT and PBC in these ABMs resembles the Decomposed Theory of Planned Behavior (DTPB) (Taylor and Todd, 1995), drawing upon constructs from the innovation characteristics literature. According to DTPB, attitude is influenced by perceived usefulness, ease of use, and compatibility, while perceived behavioral control is influenced by self-efficacy and facilitating conditions. However, the reviewed models showed less effort in utilizing these parameters dynamically, allowing them to evolve over time. Moving beyond static models, future ABMs could incorporate mechanisms for ATT, PBC, and SN to evolve. A deeper exploration of DTPB within ABMs holds promise. By incorporating the specific factors outlined in DTPB and allowing them to evolve dynamically, researchers can create more fine-grained models that capture the complexities of human decision-making within social and environmental contexts.

The reviewed studies reveal a spectrum of approaches to address how researchers translate an agent's intention into concrete behavior. Different researchers have employed various criteria for translating intentions into agent behavior within their models. In some papers (Kaufmann et al., 2009; Schwarz and Ernst, 2009; Sopha et al., 2013), it was required that intention surpass a certain threshold to trigger a behavior. On the other hand, in other studies such as the work by Kniveton et al. (2012), agents are observed to select the behavior with the highest intention among several available options, with the additional criterion that PBC must be greater than zero. Additionally, Pouladi et al. (2019) took a different approach by modeling behavior using a regression model, with intention and PBC serving as independent variables. Furthermore, Rai and Robinson, (2015) proposed that agents only take action if they surpass specific thresholds for both ATT and PBC. These diverse approaches highlight the flexibility and complexity involved in capturing the relationship between intentions and behavior within agent-based models.

Table 1-Summary of TPB parameters in different papers

Authors	Main Goal	Social network	Attitude	PBC	SN	Intention
Kaufmann et al. (2009)	spread of organic farming practices among farmers in Latvia and Estonia	small-world network	ranged from -1 (highly negative) to +1 (highly positive)	ranged from -1 (highly negative) to +1 (highly positive)	ranged from -1 (highly negative) to +1 (highly positive)	Adoption of organic farming practices
Schwarz & Ernst(2009)	Adoption of new environmental friendly technologies; Southern German	small-world network	environmental performance, ease of use, saving of costs, compatibility with existing infrastructure	compatibility with infrastructure and installation costs	percentage of installation in agent's network	Adoption of water-saving technologies
Kniveton et al (2012)	Studying future migration patterns in under climate change scenarios Burkina Faso.	small-world network	Probability values based on demographic characteristics, origin zone, and current rainfall patterns	experience of migration and assets.	consideration of the opinions of their networked peers.	Migrate to another zones
Sopha et al (2013)	The adoption and diffusion of heating systems in Norway	small-world network	fuel price stability, indoor air quality, functional reliability, total cost, required work	fuel price stability, indoor air quality, functional reliability, total cost, required work	The number of peers a household communicates with about heating systems and the network configuration.	Adoption of different heating systems
Rai and Robinson (2015)	Residential solar photovoltaic (PV) adoption, Austin USA	small-world network	home parcel size, ratio of tree-cover to size, and home value per unit size, and	home value and physical features like size, tree	_	Adoption of PV

			attitudinal heterogeneity associated with geographical location	cover, and irradiance		
Pouladi et al. (2019)	farmer decision-making regarding water use behavior in the Zarrineh River Basin, Iran	_	adjusted based on a comparison of current profits with the previous year's profits	adjusted based on a comparison of current profits with the previous year's profits	_	Adoption of different crop patterns

4. Conclusion

This review explored how ABMs leverage TPB to understand humans decision-making processes. The studies highlight the role of SN, capturing social pressure, in shaping intention. Social network structures and information exchange mechanisms can influence how SN evolves within a social network. Moreover, there is a diversity in how researchers model ATT, PBC, and SN. While some models capture these constructs as static functions of various factors, others acknowledge the potential for them to evolve dynamically based on experiences and social interactions. The reviewed studies showed various approaches for translating intention into behavior within ABMs. These approaches range from threshold-based methods to regression-based models, each with its own strengths and limitations.

Moving beyond static models, future ABMs could incorporate mechanisms for ATT, PBC, and SN to evolve based on social interactions. Further, a deeper exploration of the DTPB holds promise to add more dynamic to the model. By incorporating the specific factors outlined in DTPB and allowing them to evolve dynamically, researchers can create more fine-grained models that capture the complexities of human decision-making within social and environmental contexts. By addressing these considerations, researchers can develop ABMs that offer a more comprehensive understanding of how social interactions and individual perceptions influence behavior in complex systems. These advancements can empower researchers to explore a wider range of real-world scenarios involving social influence and decision-making, ultimately leading to more informed interventions and policies.

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