Liang, C.-L., & Collins, B. (2025). Applying Agent-Based Modeling to Examine Business Strategies – Tools and Examples for Researchers and Practitioners. *Small Business Institute Journal*, *21*(1), 16–24. https://doi.org/10.53703/001c.138368

Articles

Applying Agent-Based Modeling to Examine Business Strategies – Tools and Examples for Researchers and Practitioners

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Keywords: agent-based model, small business strategy, business decisions, sustainability

https://doi.org/10.53703/001c.138368

Small Business Institute Journal

Vol. 21, Issue 1, 2025

Scholars have noted that the business world is becoming more complex, creating new challenges for small businesses. Agent-based modeling serves as an emerging tool for small business owners, researchers, and practitioners to better manage this complexity. The purpose of this paper is to explain the fundamental concepts of agent-based modeling and share case studies where agent-based modeling has been used to enhance business and entrepreneurial strategy. Additionally, the paper will introduce two agent-based modeling toolkits, NetLogo and Repast, and it will discuss the opportunities and limitations of agent-based modeling for use in small business research.

Background

The business world involves complex decisions from interactions across participants, organizations, and government agencies. Small businesses, accounting for over 80 percent of the business world, often struggle to survive between rules, policies, and power while making risky decisions with or without proper information. Scholars have recognized the complexity of business management, 'The world is becoming increasingly challenging because the systems that need to be managed are becoming more complex. Many organizations are facing shrinking resources and growing structural complications' (North & Macal, 2007). The traditional approaches to examine such complexity involve many assumptions to reduce the burden of mathematical modeling or simulations. For example, homogeneous products or input productivity are often introduced in generating equations to simulate market behaviors in microeconomics. Unfortunately, the real market or business situations include different layers of decisions that represent producers' and consumers' preferences, objectives, timeline, planning, constraints, and consequences associated with decisions. Small business owners operate in a co-independent situation where they need to respond to market disturbance quickly while following the general norm of industry, which makes it more challenging to simulate individual business owner's behavior within an interconnected environment.

This paper shares information about using Agent-based Modeling (ABM) as a framework to support small business researchers and practitioners. The paper consists of the following sections: a literature review to summarize existing knowledge of ABM and how it has been applied in conducting business strategy research, a detailed description of the ABM framework and its components, two popular toolkits to create ABM simulations that could be applied in studying business strategies, and concluding remarks about limitations and opportunities for scholars to design and develop ABM simulations to examine small business strategies. It is not our intention to generalize the applications of ABM models given the complexity of real-world scenarios. A model framework provides a logic of thinking to support decision-making given different business operations, culture, and employer/employee relationships. This paper uses ABM model as one example to support business consultants, Small Business Development staff, and business owners to design and create effective strategies. The reliability and accuracy of the ABM simulations depend on data sources, data consistency, timeframe, and real records of business transactions, which could vary significantly across different types of businesses.

Literature Review

Introduction to ABM

Agent-based modeling (ABM) systems, developed in the 1940s and applied in political research, are a computational method of modeling the interactions between autonomous agents. ABM has also been referred to as multiagent-based modeling, agent-directed modeling, and multiagent-systems modeling (Oren et al., 2000). ABM has become increasingly popular in the academic STEM and business world, since it gained traction in the 1990's. Axelrod (1997) argued that ABM has the potential to be "a third way of doing science", and Bankes (2002) called ABM a "revolutionary development" for the social sciences. The growing popularity of the methodology has resulted in increasing numbers of journal articles, funding schemes, conferences, and educational programs that refer to ABM (Macal & North, 2009).

The proliferation of ABM is a function of many reasons. **First**, ABM systems have a wide range of applications that often involve quantitative (e.g., age, time, distance, number of workers, amount of production, etc.) and qualitative information (e.g., preferences, features, characteristics, and emotion). ABM systems have been used to model agent behavior in most STEM and business fields, including but not limited to: epidemiology, supply chains, political science, economics, marketing, resource management, and many more (Macal & North, 2009; Muis, 2010; Rand & Rust, 2011; Tesfatsion & Judd, 2006). **Second**, ABM approaches allow for a wide range of applications because 'agents' in the system are adaptable and flexible. For example, a small business owner runs a bookstore. The most common agents include the business owner, customers, employees, delivery services, and landlord for the store space. Agents can be represented and manipulated in different ways to fit whatever context the modeler chooses (Gilbert, 2019). In the bookstore example, we can define types of books available, price levels determined by the business owner, delivery schedule for the owners, and rent level defined by the landlord. We can even define types of customers whether they are college students or specialty book collectors depending on different customer profiles. **Third**, ABM frameworks and applications are fundamentally unique from other modeling structures, like variable-based or system-based structures, which provides ABM a niche for certain research projects related to small business strategies. Appropriate systems for using an ABM approach include system characteristics that model intelligent human behavior, concentrate on interactions between individuals and populations, explore changing dynamics amongst the agents, analyze how different levels in the model are related, and rely on heterogeneous behavioral rules rather than homogenous behavioral rules (Hare & Deadman, 2004; Klügl & Bazzan, 2012). These characteristics allow for the modeler to explore microscale behaviors and how those behaviors transpire throughout the rest of the model to estimate macroscale outcomes (Van Dyke Parunak et al., 1998). Rather than a traditional top-down modeling approach, ABMs take a bottom-up approach. This bottom-up approach has been called an ABMs defining feature (Epstein, 2006).

ABM Applications in Business Strategy Analysis

Traditional microeconomic simulation models are now coming under scrutiny for their assumptions of normal behavior, rationality, equilibrium, and perfect information. For example, conventional equilibrium-based economic models assume that humans and markets will act normally and rationally, making use of homogenous agents. These assumptions make sense during times of economic stability, but if there is an economic crash, both human and market behavior fluctuate away from the equilibrium. In this case, a bottom-up ABM model with heterogenous agents is better positioned to deal with unstable circumstances (Tesfatsion & Judd, 2006). Furthermore, researchers now have more powerful computers to study large-scale complex models that can integrate massive volumes of data.

Once we understand the uniqueness of the ABM approach compared with other traditional simulation methods, it would be easy to see how the ABM approach is positioned to keep growing in popularity for researchers to study business strategies. North & Macal (2007) provided a thorough roadmap to guide scholars to use ABMs to effectively examine complex business strategies and business systems. In their book, North and Macal (2007) reviewed the challenges of studying business decisions and interactions by describing the ABM paradigm compared to other simulation approaches. The ABM framework could provide a general estimate of behaviors from linkages of parts or components in the simulation scenario, considering the 'whole' beyond 'parts', and offering the comprehensive perspectives with dynamic relationships and consequences. This book also provided detailed descriptions about agents, their definitions, attributes, behaviors, conducts, and connectivity among agents. Some examples related to small business strategies are pressures of globalization, enhanced focus on information technology and data science, artificial intelligence, and times of crisis such as the Covid-19 pandemic. These are just a few contributors towards growing complexity in and outside of the business space. The ABM approach could assist researchers to simultaneously design and implement triggers to model decision-makers' interaction, reaction, and responses to multiple scenarios.

Researchers and organizations can capture the benefits of ABM in several ways. Researchers examining organizational strategies need to understand the components (i.e., individuals, circumstance, and degrees of interactions) under study and assign them behavioral rules. Once the model can be executed to translate the behaviors into results, the model can reveal how individual behaviors interact to create system-level conclusions or simulate system-level consequences. These layers of analyses are important as they link the behaviors of individual agents to the rest of the system. Therefore, researchers or organizations can study how actions at the individual level translate throughout the system (North & Macal, 2007). This allows for exploring how interventions into the system can produce positive or negative effects. Knowing how certain scenarios might play out throughout a system before actually implementing such a scenario in real life (e.g., changing the composition of an executive board, contracting with a new distribution venue) is invaluable information to any organization. Several outlets have recently noted agent-based market modeling to be a newly reputable technology for supporting decision makers in their quest for improving their entrepreneurial strategy (Rand & Stummer, 2021; Scheller et al., 2019).

Sauser, et al. (2018) applied the ABM framework to study the correlation between small- and medium-sized enterprises resiliency and community impact over time, especially when a community was recovering from a disaster. Garcia (2005) introduced the application of ABM to conduct research in innovation and product development as a part of business strategy. Three research areas were explored such as diffusion of innovations, organizational strategy, and knowledge and information flows between networks. Many scholars recognized the flexibility and adaptive nature of a system approach embedded in the ABM framework while conducting research in business strategies (Garcia, 2005; Ormerod & Rosewell, 2009). We will introduce two case studies as examples about how scholars applied the ABM in business subjects.

Case Studies Demonstrating the Benefits of ABM in Business Strategies

Consider the following case studies demonstrating the effectiveness of ABM in a business environment. An Agent-Based market simulation, such as proposed by Stummer et al. (2021), utilizes scenario analysis to explore future markets for their selected product. The authors find that ABM allowed them to have a better prediction of what future markets would look like, allowing corporate planners and industrial engineers to conduct better business strategy and have a stronger knowledge base to make strategic decisions. Scenario analysis has been praised for its ability to help companies become more flexible, proactive, and innovative because they can be prepared for future scenarios; either positive or negative (Amer et al., 2013).

The case study developed by Stummer et al. (2021) praised their created ABM for providing novel information regarding their products' (in this case, smart products) future sales under different scenarios as well as how their products market share will change over time. For example, under one certain scenario with a given set of conditions, their Product X was predicted to capture 42% of their market share compared to their Product Y being predicted to capture 23% of their market five years into the future. Running through several realistic scenarios allows for the researchers to study how different products react to certain conditions, as well as how consumers react to certain conditions. They also cite the value in researching how their customers would switch their buying behavior towards different products once new products and features were introduced into the model, noting how this information overall can lead to deriving new strategy to increase future profits.

The case study developed by Holm et al. (2018) observed how ABM can improve policy objectives within the regional wood markets of Switzerland. Once again, scenario analysis was used to see how different interventions would affect market dynamics of the regional wood industry. Scenarios that were tested looked at how the industry would react to the influences of intermediaries, profit-orientation of the forest owners, and the exchange rate. The ABM results indicated that exploring different scenarios is necessary for proper forestry planning for policy makers, as well as forest owners and businesses in the industry. Forest owners with higher profit-orientation led to more wood being sold and at higher prices. While these may benefit the forest owners in the short term, higher wood prices were found to introduce challenges to the wood processing industry which could lead to future wood industry complications.

What are the Components of an ABM?

The central component of an ABM is the agents that make up the system. Agents take on several definitions, but the core essence of an agent is that it is independent, identifiable, discrete, and capable of interacting with other agents or its environment (Bonabeau, 2002). Others argue for a stricter definition, citing that agents ought to be adaptable to its environment. For example, an agent under this sense will learn and change from their environment. In this case an agent would have a baseline set of behavioral rules, but also a proceeding set of behaviors that will be acted upon if certain conditions in the environment are met (Casti, 1997). An example of this is a tree that will grow at a normal rate under sunny conditions, but during rainy conditions it will respond by growing more quickly. One last definition requires agents to not only be responsive to their environment, but also that they must be autonomous. This would necessitate agents are not simply passive responders but active planners in their environment, such as a human being navigating their way through an airport (Jennings, 2000). Macal & North (2009) provide a structural definition for how to think about agents in an ABM in an intuitive way for students unfamiliar with agent-based modeling. Agents will have the following attributes: They are autonomous and self-directed, where they independently function in their environment. They are social, where their behavior is based upon mechanisms that describe how they interact with other agents. Lastly, they are self-contained, where agents are discrete and identifiable. Some agents may also possess traits such as being goal driven, having the ability to learn and adapt, and having resource attributes such as the number of resources each agent owns or possesses.

Toolkits for Creating an ABM

With the rise in popularity of ABM, so too has risen the number of toolkits available to create ABMs with (Abar et al., 2017). Each toolkit will offer a unique experience, with different source code, coding language, types of interfaces, operating system (OS), modeling strength and capacity for complexity, visualization capabilities, and typical domain of applications. Two of the most common toolkits that this paper will discuss are NetLogo and Repast. Each toolkit offers differing styles and benefits. Choosing which ABM toolkit to use will depend on several factors, such as the objective of the ABM, the complexity of the system, and programming capability of the modeler. Both NetLogo and Repast are free to download and do not have any proprietary licensing.

NetLogo Background

NetLogo is commonly selected as the first toolkit for a novice modeler to use. This is because of its relative ease of use, strong source of educational tools, documentation, and tutorials, and its ability to run on all operating systems and platforms. In a review of five of the most common ABM toolkits, Railsback et al. (2006) praised NetLogo as the easiest to use and learn, highlighting its intuitively simple programming language and its useful graphical interfaces which helpfully illustrate components of the model both while the model is being designed and while the model is running. NetLogo was specifically built to model natural and social systems, where it was to be used for both educational and research purposes (Tisue & Wilensky, 2004). The toolkit was developed by Uri Wilensky in 1999 and is currently being administered by researchers at Northwestern University's Center for Connected Learning and Computer Based Modeling (CCL). An active online NetLogo discussion group provides a space for questions and answers for modelers within the community. NetLogo's creators aspired to design an ABM capable of modeling both complex simulations which could be used by experienced modelers as well as modeling simple simulations to be created and used by beginner modelers. Due to its widespread application to a diverse set of modelers, Netlogo has been downloaded tens of thousands of times and has been used to help teach modeling in computer science and modeling classes at several universities (Gammack, 2015; Railsback & Grimm, 2019).

How to Use NetLogo

NetLogo can be installed from the following website https://ccl.northwestern.edu/netlogo/. Upon opening the program, the user will notice three environments that are available to interact with. These are the programming environment, the visualization environment, and the documentation environment. The user will write and edit their NetLogo code in the programming environment. The visualization environment shows both the setup of the model, as well as the moving parts of the model as it runs. The user has the potential to see how their agents interact and how the model's metrics change as the model runs. In the programming environment, the user has the option to add interface buttons which can be seen in the visualization environment. Examples of interface options include sliders to change variables in the model more easily, or monitors to more closely and easily observe tracking variables as the model runs. The documentation environment is where educational documentation about the model can be found. If running a model created by someone else, such as running one from the NetLogo sample model library, the documentation environment houses information on that specific model's development that is important for the user to know. Modelers creating their own model are encouraged to add details to the documentation environment for how to run their model correctly.

NetLogo is generally an excellent option for creating models with few sets of agents. This is because NetLogo executes its code off only one script, which makes modeling the interactions between more than only a couple agents very tricky. Because there is only one script of code, each interaction between sets of agents must be manually coded for. For this reason, NetLogo is preferred for working with systems that are on the scale of marginal complexity. The NetLogo programming language stems from the Logo language, which was designed to have a low threshold for learning the language specifics. The NetLogo language's syntax is described as easier to learn due to its simplicity compared to object-oriented languages, which are used in other ABM toolkits such as Repast (Lytinen & Railsback, 2012). Additionally, NetLogo has a useful syntax checker button that recognizes most errors in the code without having to run the model, offering a user-friendly approach to editing lines of code in an efficient manner.

Applications of NetLogo

Scholars across diverse scientific disciplines have used NetLogo as a key research tool. Projects using NetLogo have ranged from looking at food desserts (Gebrehiwot et al., 2022), to analyzing the immune system to inform biomedical research (Chiacchio et al., 2014), to simulating animal foraging behavior (Zhang et al., 2022). Shen & Zhou (2023) used NetLogo to explore how social behavior impacts the recycling of express packaging by building a model to better understand the factors at play that either encourage or discourage citizens to recycle. In addition to this host of fields with applications to NetLogo, there are several examples of business scholars using NetLogo to analyze business and entrepreneurial strategies.

One common field within business is using NetLogo to simulate supply chains and measure upstream and downstream effects of the actions of supply chain stakeholders. To understand the dynamic nature of supply chains, Christos et al. (2016) used NetLogo to test its capability for enhancing decision making in the supply chain process by creating a model of a dual-source grocery retailer. Grocery products are given attributes based on their freshness which declines over time, with the freshest quality items being sold at a high price and deteriorated products sold at a lower price. The grocery retailer is connected to two supply chains, where one supply chain is more expensive, local, and can deliver products more quickly, and the other supply chain is lower cost, non-local, and requires larger ordering volumes to move products. The model tracks the following variables as it runs: procurement costs, lost sales costs, number of products sold to customers, and total revenues. The authors concluded that NetLogo performed well in outlining how supply chain stakeholders can reduce costs and increase flexibility by testing different scenarios and seeing how the ripple effect upstream and downstream of the supply chain.

De la Fuente et al. (2017) advocate NetLogo as an option to enhance entrepreneurial strategy by examining business scenarios with business prototyping. Business prototyping is a methodology to improve decision making by simulating real-world business issues to test new business ideas and policies in order to gain a competitive advantage. By prototyping business ideas in a virtual environment, ideas can be vetted prior to being implemented in the real world, forgoing the risk and costs of real-world experimentation. The authors use NetLogo to model the newsvendor problem (Qin et al., 2011), which is an exercise for business managers to determine the optimal rates for ordering perishable products when demand for those products is ambiguous. The newsvendor can represent any business with a product to sell. The newsvendor interacts with consumers, distributors, and other market signals and noise that affect demand, selling price, and production cost. The output function of the model measures net profit. Several management strategies that weigh variables differently led to finding strategies that produced the most net profit.

NetLogo has also been studied by business scholars for its applications in logistics analysis to improve business process management. Using an example of a hospital emergency department, Sulis & Di Leva (2018) used NetLogo to see how agent-based models can inform business managers for optimizing business processes. NetLogo was used to create an environment to uncover logistical inefficiencies and bottlenecks, where the ABM user could then explore different management scenarios to mitigate these issues. Examples that the NetLogo model found to optimize logistical efficiency in this case study were to modify workload for each employee as well as shift roles in the workforce, which led to shorter wait times and less overcrowding in the hospital emergency department. The authors note that this approach can be extended to improve logistical efficiency in several business applications that rely on a workforce providing a service where time needs to be optimized.

Repast Background

The Recursive Porous Agent Simulation Toolkit (Repast) is an alternative option for creating ABMs and can be installed for free at https://repast.github.io/. Repast was developed in 2000 at the University of Chicago by Sallach, Collier, and others (Collier et al., 2003). After development, Repast has been administered through Argonne National Laboratory, given the lab's vast computing resources and talent available. Development has primarily been through Argonne National Laboratory, yet several groups such as the University of Michigan have contributed towards Repast's advancement. Repast was originally designed to support "rapid social science discovery" (Sallach & Macal, 2001) and has been used in several small-scale and large-scale modeling applications, ranging from evolutionary biology to market modeling (North et al., 2013).

Three versions of Repast exist, each with its own subset of relevant uses. Repast Symphony, last updated December 2022, is a java-based application that is the easiest to learn and use on singular workstations such as a laptop or desktop. Repast for High Performance Computing (Repast HPC), last updated October 2021, is the variation that uses 'expert-focused' C++ based coding for use with large clusters of computers and supercomputers. This variation would be suitable for models requiring extremely large data sets but would likely not be accessible to the average independent user. Lastly, Repast for Python, last updated October 2023, is the newest version in the Repast suite. Repast for Python is a python-based toolkit to help bridge researchers to create large-scale ABMs. This paper will primarily discuss Repast Simphony given its stronger applicability to the world of business.

How to Use Repast

The toolkit was created with an emphasis on abstractions and modularity. North et al. (2013) stated several of the design aspirations of Repast Simphony in development. First, the toolkit includes a strong separation between the model's specification, execution, visualization, and storage. Second, the toolkit focuses on automation to reduce the number of tasks that are often deployed manually by model developers. Third, all of the model's components are java-based, ensuring the objects are able to integrate with external software and allow for plug-ins to customize model development. A few other specifications into development emphasize using shorter scripts to reduce 'boilerplate' code and maximize simple and direct coding. Whereas the NetLogo toolkit is all housed in its own environment, Repast uses Eclipse as its development environment. Eclipse is a popular development environment given its strong integration with the Java language and allowance of visualization windows.

Despite its familiarity within the ABM community, Repast Simphony is less popular and less intuitive than NetLogo, and has far fewer learning resources available. However, the benefit that Repast provides for allowing for more complex modeling is that it allows for more agents and interactions through its object-oriented programming approach. This is primarily because of how Repast is structured. Repast runs off multiple combined scripts, where unique scripts can be created to represent agents, environments, or links between agents. This modularity in scripting is extremely useful and inherently more valuable for introducing several agents into a model compared to the structure used in NetLogo. This modularity also allows for watch-based scheduling or unconditional scheduling, where the Repast model can run different components of the model at designated time points allowing for modelers to scale their model up from sequential execution to concurrent or parallel execution as their model increases in complexity (North et al., 2013). The modular approach can also improve execution speed, where Lytinen & Railsback (2012) stated that Repast has a reputation of having quicker execution speeds than NetLogo.

Repast Applications

Example Repast applications include analyzing ecological conservation practices (Daloğlu et al., 2014), modeling cost-share programs to improve water management strategies (Sun et al., 2021), and forecasting the effects of changes in agricultural policy to farm production (Kremmydas et al., 2015). Repast's object-oriented modeling approach has been noted as an excellent tool to assist with Comprehensive Situational Mapping to improve strategic decision making (Druckenmiller et al., 2004). The authors demonstrated Repast's effectiveness at helping decision makers manage uncertainty by analyzing how threats to business could impact consumer demand. Using the example of a tourist agency, the model analyzes how a terrorist threat might impact business through decreased consumer desire to engage with tourism. The initial threat has downstream effects throughout the entire tourist industry, which can be used for decision makers to properly mitigate negative effects. For effective business management, Repast has also been used for finding optimum ways to deal with organizational necessities such as proper waste management. Ding et al. (2016) created a model for organizations to improve their waste management strategy by quantifying their waste, analyzing the organizations relationship with waste stakeholders, and exploring mechanisms to change rates of waste sent to landfills or recycling plants.

For assisting with organizational management, Du & El-Gafy (2014) identified Repast as an ideal tool to use ABMs to model complex business systems. Using the case study of the construction industry, the authors used Repast to develop the Virtual Organizational Imitation for Construction Enterprises (VOICE) model. Models of organizational behavior which outlined the contributing factors towards employee, group, and organizational performance provided the foundation for the model. Project-based organizations, such as in the construction industry, rely on several factors to improve the performance of their projects, such as project priority, complexity, time limit, cost limits, and chances of mistakes. Project teams are modeled as agents and are given attributes such as competence, work quality, work capacity, stress capacity, and salary rate. The authors note the complexity of attempting to model all of these interacting factors, acknowledging that their model is a work in progress to fully capture the complexity of organizational management. Yet they conclude it is a starting point for business decision makers to explore how micro-level behavior processes relate to collective performance.

Discussions and Limitations

Although ABM takes a systematic approach to help business make balanced decisions, there are limitations about the modeling structures and assumptions that need to be addressed:

1. There are over 700 categories of industries in the U.S. Each industry includes diverse business entities in terms size of employees, scale of earnings, networks of vendors and consumers, geographical profiles, and social/environmental orientations. Each business also has a different mission, vision, and goals depending on its culture, legacy, and values defined by people working within the domain. Any ABM model needs to have a clearly defined domain of people, environment, and explicit circumstances to achieve the research goal. For example, a small fruit and vegetable farm is very different from a large livestock farm in the way they run the farm, how they sell their products, who they approach for funding support, and why they approach to seek technical assistance. The ABM configurations for these two farms will be significantly different as we define factors, characteristics, and constraints when simulating business strategies.
2. Since ABM's advantage is from the system perspective, it would be important to identify proper situations to apply ABM without overlooking key aspects in research. For example, if a restaurant owner contacts the Small Business Development Center to get some help with market expansion, we need to know what the owners want to achieve – to gain more customers for the existing business, open a second business, or increase advertising and promotion activities. Different types of business strategies could be simulated by ABM, however, one ABM should focus on one goal to start with. It is possible to integrate multiple ABM simulation systems into a large, dynamic system framework. However, from the practical aspect, starting with a single purpose could reduce confusion for business owners before things get too complicated.
3. Many businesses have introduced 'sustainability' in their mission. Sustainability involves social, economic, environmental, and equity aspects. An ABM simulation has the advantage of incorporating factors and characteristics associated with sustainability. However, some attention needs to focus on whether the expected outcomes relate to discrete or continuum decisions. For example, if the goal of the simulation is to help a business improve revenues over three years, the ABM's variables such as input costs, sales per month, payroll, insurance, and tax might have conflicting effect when more pollution or waste could also be generated in three years. Tradeoffs and unintentional consequences might not be generated directly from the ABM's results. Additional interpretations would be important.
4. To adequately model a small business requires extremely detailed knowledge about the business. For example, creating agents that sufficiently represent a business's consumers necessitates having a great understanding about the business's consumer behavior. Knowing the consumer's subjective knowledge, objective knowledge, and experiential knowledge are all critical to generating a model that produces reliable results when producer-consumer interactions are involved (Vigar-Ellis et al., 2015). How, for example, might a modeler choose to represent synthesizing a consumer's singular preference into group consensus? What generalities can be made about consumer groups without stripping down unique traits about individual consumers? Balancing the desire to capture the full complexities of the business while understanding that no model can perfectly capture reality will pose a challenge to any business owner. All models will have a certain number of assumptions, however it is up to the modeler to make difficult decisions about which assumptions to accept. Modeler's must understand that no model is perfect. It is useful to recall the famous quote from statistician George Box stating "All models are wrong, but some are useful."
5. One final challenge for researchers and practitioners who would like to participate in ABM is the reality that a certain standard of coding skill is required for proper implementation. While coding mastery will be superfluous to many business ABM applications, knowing the basics of coding principles is necessary to model the creation and interaction of agents and their environment. NetLogo offers a reasonable accommodation by offering less of a barrier to novice

coders through its relatively simple Logo code and its surplus of training materials.

Conclusion

There are numerous simulation models that have been designed, created, and applied in business strategic analyses. The ABM modeling systems offer a relatively flexible way to simulate the activities (e.g., buying and selling), interactions (e.g., producers vs consumers), and consequences (e.g., profit vs loss) in the real business world. Compared to the traditional microeconomics approaches, the ABM models allow integrated factors and characteristics representing different agents in various scenarios and decision-making procedures. There are pre-programmed tools, free of charge, such as NetLogo and Repast available for researchers and practitioners to apply. The applications of the ABM simulations would significantly improve the effectiveness of business strategy analyses associated with workforce development, hiring and retaining employees, assignment of roles and responsibilities, distribution channels, communication patterns and styles, transportation schedule, and many other aspects in business operations.

In this paper, we have introduced both ABM concepts and ABM case studies demonstrating their effectiveness in small business strategy and research. While there are several existing examples of ABM and business integration, we advocate that there is great opportunity for researchers and practitioners to further explore this relationship. Useful business strategies such as scenario analysis and business prototyping offer a glimpse into novel ways that ABM can assist business owners in their operations. While emerging possibilities with the integration of ABM and business strategy are exciting, some limitations may act as a barrier for researchers and practitioners.

1. Substantial knowledge about every aspect of one's business is necessary to adequately model in an ABM. There needs to be sufficient amount of data that support/validate production, market, supply chain, or other transactions in different scenarios. It is important to use ABM to simulate one scenario at a time for new users (e.g., one business in one community as a start-up status). Once the simple model is established, the same framework could be expanded to introduce more complex interactions and transactions.
2. Each business is unique which means that every ABM will be unique. Different types of products, for example, need to be coded separately in the ABM agent specification stage because each product would have different types of buyers.
3. Knowledge of coding could be a barrier for users. There needs to be some familiarity of coding in an ABM framework to clearly and consistently identify agents/actors, interactions, and consequences.
4. Finally, all modelers must understand that no model is perfect and insights from one type of the model must be put into the context of the model itself. Generalization would lead to misrepresentation and confusion when it comes to strategic analyses.

Submitted: August 25, 2024 MDT. Accepted: January 27, 2025 MDT. Published: June 30, 2025 MDT.

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