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Complexity in the humanities and the humanities in complexity

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In this paper, we discuss the relationship between agent-based modeling (ABM) and humanistic complexity, a relationship that is often overlooked in most ABM research as it is commonly practiced. However, when we situate ABM within a broader intellectual context, we find that it is gradually moving toward, or uncovering, its humanistic dimension of complexity. In this article, we draw on the respective "*turns*" in the philosophy of science and the history of science to articulate this intellectual context, and from this perspective we can discern the driving forces behind the shift from equation-based modeling (EBM) to ABM. Put more poetically, ABM enables scientists to confront what might be called *the unbearable lightness of science*, a challenge that this paper refers to as *the return of weight*. From the vantage point of this "return of weight," we revisit key milestones in ABM and the burdens it currently struggles to bear. We argue that if ABM is to shoulder even greater weight, its next step must inevitably engage with the *consilience* of science and the humanities as advocated by Edward Wilson. Yet to achieve this, a breakthrough in computational power is required. Today's revolution in computing provides precisely such an opportunity, enabling ABM to carry greater humanistic weight and thereby enhance the realism of simulation.

KEYWORDS
agent-based modeling, autonomous agents, consilience, generative AI, humanistic complexity

1 Motivation and an overview

A long-standing aspiration in social simulation is to represent human behavior with sufficient realism to illuminate complex social phenomena. Over the past several decades, agent-based modeling (ABM) has been widely regarded as a major step forward in this respect, as it allows researchers to move beyond aggregate representations and to model heterogeneous individuals, localized interactions, and emergent macro-level outcomes. Yet despite these advances, a persistent gap remains between the behaviors generated by social simulations and the richness of actual human behavior—a gap that has often led critics to characterize much social simulation as retaining a "toy-like" character (Wolfson, 2009).

This limitation becomes particularly evident when one considers the psychological, emotional, and cultural dimensions of human life. While contemporary simulations increasingly incorporate bounded rationality, learning, social influence, or simple behavioral heuristics, the complexity of real human cognition and motivation often exceeds what such models are able to capture. Even at the frontier of current developments, the complexity of actual human psychology and behavior still far surpasses what social simulation has thus far been able to represent (see Sections 5.3 and 6).

How, then, do we become so acutely aware of this gap? Our awareness arises not only from empirical observation of the societies we inhabit, but also from insights long cultivated within the humanities, and literature in particular. For centuries, literary works have explored individuality, inner conflict, memory, emotion, moral reasoning, and the context-dependent transformation of the self—dimensions that remain difficult to formalize within computational models. In this sense, literature may be regarded as an alternative form of social simulation, one that has long surpassed silicon-based simulations in its ability to represent human complexity (Section 2).

This recognition leads to a paradoxical question. If, relying solely on human intellect rather than computation, we have already been able to grasp the complexity of the human condition through literary imagination, can advances in computing power, algorithms, and data truly enable social simulation to overcome this limitation? Will the bottleneck in representing human complexity be resolved by the technological "trinity" of algorithms, computing power, and big data, or does it point to deeper conceptual limits? Put provocatively, can we imagine works such as *War and Peace*, *The Brothers Karamazov*, Shakespeare's great tragedies, or *Dream of the Red Chamber* emerging from silicon photonics or quantum computing (Section 6)?

Although this essay undertakes a reflective review of how "human complexity" is currently addressed in social simulation (Section 5), it does not aim to offer predictions or prophecies. Rather, it revisits a long-standing question that inevitably resurfaces as models grow increasingly sophisticated: will future literature yield its world to simulation, or will it continue to reign supreme? Can human complexity ever be captured by technologies other than pen and paper?

Framing the problem in this way situates social simulation within a broader dialogue with the humanities (Section 2). From this vantage point, we examine how social simulation—particularly in the form of ABM—has gradually moved toward greater humanistic depth through a series of intellectual and methodological shifts (Sections 3 and 4). Tracing this trajectory allows us to reinterpret the historical transition from equation-based modeling (EBM) to ABM as a gradual "return of weight," in which individuality, heterogeneity, and meaning are reintroduced into scientific explanation (Section 5).

Before proceeding further, it is important to clarify the scope of this paper. First, we use agent-based modeling (ABM) to represent the broader domain of social simulation. While we recognize that equation-based modeling (EBM) constitutes another major branch, this paper deliberately confines its discussion to ABM—not only because ABM has become the most widely used approach in contemporary social simulation, but also because the roles, identities, and behavioral patterns of agents are difficult to develop fundamentally within EBM, which largely abstracts away from individuals (Sections 3 and 4).

Second, the intertwining of social simulation and the humanities is not entirely new. As discussed later, it may be viewed as part of the broader intellectual movement toward *the consilience of knowledge* advocated by Edward Wilson (1929–2021) (Wilson, 1998), though with important qualifications regarding the relationship between science and the humanities (Section 6). In this respect, the present paper contributes to ongoing discussions in complexity research by revisiting the humanistic dimensions of social simulation and by exploring how recent advances in computational power may enable ABM to carry greater humanistic weight.

The rest of the paper is organized as follows. Section 2 revisits the nature of humanistic complexity in relation to scientific complexity and clarifies the meaning of the paper's title. Section 3 outlines two intellectual shifts—the philosophical turn from deductive to generative explanation and the scientific turn from single-level to multi-level models—that together frame the rise of ABM beyond the limits of EBM. Section 4 examines why equation-based models could not accommodate these shifts, drawing on Murray Gell-Mann's notion of agent-based mathematics. Section 5 illustrates how ABM overcomes the "unbearable lightness" of EBM by reintroducing "weight" at progressively deeper levels, from parametric variation in ecology (Sec. 5.1), to ascribed group identities in Sakoda's models (Sec. 5.2), and acquired traits in Axelrod's model of cultural dissemination (Sec. 5.3). Section 6 advances the idea of a new kind of heft grounded in the convergence of ABM and literature, enabled by recent advances in computational power. Section 7 concludes by reflecting on how ABM may serve as a bridge between scientific rigor and humanistic depth.

2 Humanistic complexity: at the pinnacle of complexity

When considering the significance of the emergence of agent-based modeling (ABM) for the humanities, and more broadly for social simulation, it is essential to first reflect on the special status of what may be called *complexity in the humanities*. We argue that this form of complexity occupies a supreme position, representing the very pinnacle of complexity itself. To put it differently, a genuine understanding of "complexity" cannot be attained without entering the perspectives and domains of the humanities; without some degree of humanistic enlightenment, it is difficult to claim any profound comprehension of the concept.

This line of thought is not entirely unfamiliar. The social philosopher Auguste Comte (1798–1857) proposed a "six-story" hierarchy of the sciences (Comte, 1875)[1], while Warren Weaver (1894–1978) later introduced a "three-story" model (Weaver,

Abbreviations: ABM, Agent-Based Modeling; EBM, Equation-Based Modeling; GPU, Graphics Processing Unit; TPU, Tensor Processing Unit; LLM, Large Language Model; NLP, Natural Language Processing; NOMA, Non-Overlapping Magisteria.

1 In his magnum opus *Cours de philosophie positive* (*The Course of Positive Philosophy*, 1830–1842), Auguste Comte arranged the sciences in a logical sequence from the simplest and most general to the most complex and particular, dividing them into six levels. From the bottom up, these were: Mathematics, Astronomy, Physics, Chemistry, Biology, and Sociology (which he at the time called "*Social Physics*"). Comte argued that the higher sciences often rely on the methods and results of the lower ones, but deal with phenomena that *are more complex and variable*. Thus, the higher one ascends in this hierarchy, the closer one comes to the complexities of human society and the humanities.

1948)[2]. Both frameworks placed the natural sciences at the lower levels and the social sciences higher up. Yet, in their time, the so-called "soft sciences" likely did not include the humanities. Were the humanities to be incorporated, we contend, they would necessarily be positioned above the social sciences–at the very summit of complexity.

A similar view has already been advanced by others. In *Cents and Sensibility: What Economics Can Learn from the Humanities*, Morson and Schapiro (2017) adopt an unusually humble stance for economists, setting aside economics' self-image as the queen of the social sciences and instead asking why economics might learn from the humanities. Their answer lies in the degree of complexity with which the humanities are concerned, a complexity far greater than that addressed either by the natural sciences or by the social sciences influenced by natural science methods.

First, the humanities address phenomena that are highly *narrative* in nature and extremely resistant to formalization, whether mathematical or quantitative. Economics typically assumes that human preferences are given and fixed, reducing individuals to actors who maximize quantifiable utility. By contrast, the humanities emphasize narrative, meaning, and value construction: they investigate how values are formed, challenged, and transformed, insisting that human beings "live in stories," shaped by the narratives they construct for themselves and others. Economic models stripped of narrative context risk fundamental misunderstandings of human behavior. Second, the humanities give primacy to individuality, particularity, contingency, and context-dependence. Singular events, distinctive personalities, and cultural factors may redirect the course of history or reshape personal destinies. Such phenomena resist simplification into probabilistic models or reduction to statistical generalizations. Instead, they require interpretation, comparison, and critique in order to be more deeply understood.

Thus, the humanities can provide a richer and more layered account of human motivation than the overly thin assumptions of *homo economicus*. Such an account encompasses not only emotion, identity, and social responsibility but also moral reasoning. This broader perspective enables us to anticipate *unintended consequences* of decisions or policies, particularly when they touch on issues of justice, dignity, fairness, or cultural meaning, where the insights of the humanities are indispensable. In short, Morson and Schapiro remind us that only by engaging with the complexity of the humanities can economics hope to grasp and respond more fully to the multi-layered realities of human life.

In *The End of Theory* (2017), Richard Bookstaber advances his critique of standard economic modeling by invoking the notion of 'radical uncertainty,' thereby highlighting the distinctive role of literature in capturing the open-ended transformation of human experience. He writes: "If we change with our experiences, and if we cannot anticipate those experiences or how they will change us, if we must live out life in order to know it, then a central underpinning of economics is ripped away. Neither economics nor psychology nor cognitive science expresses this notion of radical uncertainty. It is rooted in the humanities, in our sense of self, rather than in science. *So I look for its expression in literature*." (Bookstaber, 2017, p. 60; Italics added).

If readers can accept the argument advanced above, namely, that *complexity in the humanities* represents the highest form of complexity, then the second part of this paper's title, *the humanities in complexity*, follows as an inspired direction for further development. More specifically, it points to a new orientation for modeling: the idea that models ascend to a higher level of complexity when the humanities are incorporated into them. Put simply, models attain genuine complexity only when the humanities are brought into the modeling enterprise; this marks the true beginning of complexity in modeling enriched by the humanities.

This, however, raises a paradoxical question: Is there any space within models for the humanities, especially for complexity in the humanities? Regrettably, the traditional answer has been "no." More precisely, throughout the long course of human history, the answer has been "almost not yet." Recent developments, however, have begun to change this situation with the rise of *computational social science* (in particular, *agent-based modeling*) and the advent of *big data* (Gilbert, 2010). Looking ahead, advances in *generative AI* and *natural language processing* make such integration even more feasible. This paper will explore how these developments create new possibilities and, as a contribution to this special issue, will focus on complexity in the humanities, with psychology serving as one important perspective among others.

3 ABM: the convergence of two turns

In the last century, both the philosophy of science and the history of science underwent important shifts. In *the philosophy of science*, the central question—what constitutes a scientific explanation—remained the same, but the dominant answers shifted from *deductive* to *generative explanation* (Sec. 3.1). In *the history of science*, by contrast, there was *a micro-level turn*, emphasizing small-scale, localized, and contextual analyses (Sec. 3.2). We will explain these shifts in sequence below.

3.1 The philosophical turn: from deductive to generative explanation

In the philosophical shift within the philosophy of science, methodological individualism and abductive reasoning came to the forefront. *Abduction*, as Charles Peirce (1839–1914) originally described it, refers to the inference that generates explanatory

2 Warren Weaver divided the development of twentieth-century science into three levels. First, from roughly the seventeenth century to the early nineteenth century, the scientific focus was on *the problems of simplicity*: systems with only a few variables that could be precisely described by mathematics (such as Newtonian mechanics or planetary motion). Second, from the late nineteenth century to the early twentieth century, attention shifted to the problems of *disorganized complexity*: systems with a very large number of variables, but without strong coupling among them, making them amenable to statistical treatment (such as the kinetic theory of gases or statistical mechanics). Finally, Weaver argued that the problems of *organized complexity* became the central scientific challenge after the mid-twentieth century: systems composed of many interacting and structured parts (such as biological, social, and economic systems), which require interdisciplinary approaches and new theoretical tools.

hypotheses (Peirce, 1883, 1931–1958). Later, Tony Lawson, drawing on *critical realism*, adopted the term *retroduction* to emphasize reasoning toward underlying generative mechanisms (Lawson, 1997, 2003, 2019). Both approaches highlight a turn away from purely deductive explanation toward more generative accounts. A satisfactory explanation cannot remain at the level of describing macro-regularities; it must go beyond appearances, probing into the micro-level and hypothesizing about *generative mechanisms* that may not be directly observable yet potentially underlie the phenomena. For example, in Joshua Epstein's notion of *generative sufficiency* (Epstein, 2006), if we can specify a set of micro-level rules and, through simulation, generate macro-level outcomes consistent with reality, then we may be said to have offered an explanation.

The sociologist James Coleman (1926–1995) visualized generative explanation with the image of a "boat," commonly referred to as *Coleman's Boat* (Coleman, 1990). In Coleman's framework, he was not only concerned with how macro-level phenomena emerge from individual interactions, but also with how the macro level feeds back to influence individuals—a process often described as *downward causation* (Sawyer, 2009). A genuine explanation, in his view, must begin with macro-level conditions, such as institutions, social norms, or cultural environments, and then move downward to the level of individuals, showing how these macro structures shape their preferences, beliefs, and possible courses of action. It must then go on to demonstrate how interactions among individuals unfold in specific contexts, before finally returning to the macro level to generate new social outcomes. The essence of this "boat," therefore, is that macro-level effects must be mediated through the micro-level in order to produce macro-level results. For this reason, it is also known as the *micro–macro link*[3].

In fact, even before Coleman's "boat," the founder of institutional economics, Thorstein Veblen (1857–1929), had already articulated a similar insight. In *The Theory of the Leisure Class*, Veblen observed that institutional change, in turn, selects individuals endowed with temperaments and habits best adapted to the environment; these individuals then further adjust to the environment and, through their actions, create new institutions. This observation resonates with Coleman's argument, as both emphasize the bidirectional causality between the macro and the micro. The true driving force of social development, in this view, is a cyclical process.[4]

3 The micro–macro link is a central concept in sociological theory, arguably almost a meta-concept, widely applied across a variety of theoretical and empirical studies in sociology (Alexander et al., 1987; Raub and Voss, 2017).

4 Here is the full quotation: So that the changing institutions in their turn make for a further selection of individuals endowed with the fittest temperament, and a further adaptation of individual temperament and habits to the changing environment through the formation of new institutions. The forces which have shaped the development of human life and of social structure are no doubt ultimately reducible to terms of living tissue and material environment; but proximately for the purpose in hand, these forces may best be stated in terms of an environment, partly human, partly non-human, and a human subject with a more or less definite physical and intellectual constitution. (Veblen, 2009, p. 125).

3.2 The scientific turn: from single-level models to multi-level models

As for the micro-level turn in the history of science, more and more fields have come to recognize that in constructing systematic knowledge, they must take into account the individuality, particularity, heterogeneity, and spatiality (location/space) of the components within a system. Single-level models can no longer satisfy this demand; instead, modeling must shift toward approaches that integrate both the macro and the micro, or what are often called *multi-level models*. Take ecology as an example. As early as the 1970s and 1980s, there was a growing aspiration to bring into models the specificity, diversity, and geographical embeddedness of animals and plants through *a bottom-up approach*. This pursuit gained clear momentum in the 1990s and 2000s. For reviews of this development, see Huston et al. (1988), DeAngelis and Gross (1992), and Grimm and Railsback (2005).

A similar turn occurred in epidemiology between 2000 and 2010. Traditional approaches to infectious disease were *top-down*, focusing on a few state variables or parameters, such as the proportion of infected individuals, the probability of recovery among the infected, the proportion of the susceptible population, and their probability of becoming infected. Yet such aggregate treatments clearly could not capture the individuality of each person—their psychology, behavior, culture, or spatial heterogeneity—that might directly or indirectly shape the course of contagion. Indeed, as the recent Covid-19 pandemic vividly illustrated, individual-level factors such as preventive behavior, medication practices, and patterns of social interaction all contributed, in both direct and indirect ways, to the dynamics of disease transmission. In light of this, public health and epidemiology have increasingly moved toward bottom-up approaches that link the micro and the macro (Auchincloss and Diez Roux, 2008; Arifin et al., 2016; Simler, 2020; Stevens, 2020).

The urgency of this demand was captured with great clarity by physicist Auyang (1998), who posed the incisive question: "How do we explicitly represent the composition of a large system while preserving the integrity of the system and the individuality of its constituents?" (Ibid, p. x). This question highlights the delicate balance between individual-level representation and system-level representation. On the one hand, how can we preserve the individuality of the constituent elements without erasing or oversimplifying them? On the other hand, how can we pursue this preservation without losing the coherence and integrity of the system as a whole? Put simply, we must avoid both "seeing only the trees but not the forest" and "seeing only the forest but not the trees."

This challenge of "seeing both the trees and the forest" reappears in economic theory in a more familiar form—namely, the long-standing question of whether macroeconomics requires microfoundations. Here, the debate divides into *methodological holism* and *methodological individualism*. The former, exemplified by the older traditions of Keynesian macroeconomics, maintains that "the macro is the macro, and the micro is the micro"—that the study of aggregate phenomena need not be grounded in the behavior of individuals. Even today, many still hold this position (King, 2012). The latter, by contrast, emerged forcefully with the *rational expectations revolution* of the 1970s and gave rise to new classical macroeconomics (Begg, 1982; Galbács, 2015). This school insisted that macroeconomic analysis must begin from individual rationality.

Yet, the "rationality" assumed in these models bears little relation to Kantian philosophy or to any conception of human beings as spiritual, moral, or religiously motivated creatures. Instead, the economic agent–the proverbial *homo economicus*–is reduced to what Deirdre McCloskey once memorably called a "Max U machine," a device for maximizing utility (McCloskey, 2010). She employs this metaphor to point out that the human behavior assumed in mainstream economics is overly mechanistic, lacking the humanistic dimensions of morality, culture, language, and history. Thus, while today we debate whether human beings might one day be replaced by machines or AI, in the world of economic models that replacement arguably occurred long ago (Chen, 2021).

3.3 The turn to ABM

When these two intellectual shifts are placed side by side, their resonance becomes clear. Philosophers emphasize that a satisfactory explanation must uncover the generative mechanisms at work, and that such explanations must pass through the level of the individual in order to account for macro-level outcomes. Scientists, meanwhile, in their efforts to overcome the limitations of traditional system models, have been compelled in practice to confront the integration of micro- and macro-level processes. Taken together, the former provides the justification for agent-based modeling (ABM), while the latter establishes its necessity. And these dual shifts—especially the latter—open a broad avenue for the humanities to enter the domain of complexity modeling, thereby enhancing the possibility of representing real human behavior within social simulations.

4 ABM: in relation to the emergence of EBM

At the end of the twentieth century, a new approach to modeling emerged within the study of complex systems, referred to as *agent-based modeling* (ABM). The notion of ABM can be traced back to Nobel Laureate in Physics Murray Gell-Mann (1929–2019), who introduced the term in his book *The Quark and the Jaguar* (1994).[5] In his book, Gell-Mann draws a distinction between traditional equation-based modeling and what he terms "*agent-based mathematics.*"[6] He begins with discrete mathematics, emphasizing that it should no longer be regarded merely as an approximation of differential equations, but as a methodological framework in its own right for the study of complex adaptive systems. He illustrates this point with examples such as interactions among organisms, investment decisions, and generational turnover, thereby demonstrating how the dynamics of a system may be represented using only a limited set of discrete state variables. He then further specifies "rule-based mathematics" as what he terms "agent-based mathematics," identifying TIERRA (Thomas Ray's artificial life simulation system) as a paradigmatic case.[7]

Why does Gell-Mann recommend agent-based mathematics to us? The reason, in fact, has something of a "humanistic" character (Gell-Mann, 1994, pp. 320–325). Put simply, agent-based mathematics allows us to confront the "bounded rationality" that we are forced to reveal in a complex world. In other words, it provides a way to represent *humanistic complexity* through appropriately constructed models, enabling us to read *the human within complexity* from the models themselves (Chen, 2024). Here Gell-Mann not only points out that "rationality" is neither the sole nor necessarily the most important factor in agents' decision-making, but also suggests more provocatively that the very motivation for relying on "rational" models may stem from a desire to escape from complexity (Chen, 2024).

This is so because the difficulty of addressing the aforementioned Auyang's "forest and trees" problem depends on *the degree of heterogeneity* among individuals. When heterogeneity is low, the challenge is relatively easy; when heterogeneity is high, the challenge becomes much more daunting. Within the constraints of equation-based mathematics (EBM), new classical macroeconomics sought to simplify matters by assuming *low heterogeneity*, often treating individuals as if they were essentially the same.

Here, Gell-Mann's "rationality assumption" conveniently provides a solution: when everyone is "designed" as fully rational, then through the logic of "*if minds are alike, reasoning is alike*," heterogeneity is gradually erased and heterogeneous individuals are transformed into homogeneous ones. At this point, the era of the "*representative agent*" arrives (Hartley, 1997; Gallegati and Kirman, 1999), where the forest and the trees collapse into one—the forest becomes the trees, and the trees the forest. In this way, the very complexity that Auyang identified as a central challenge seems neatly resolved, though only by abstraction rather than by engagement with true heterogeneity.

However, one of the defining characteristics of the humanities is precisely the complex heterogeneity of individuals, that is, heterogeneity across multiple dimensions. On the one hand, the very question of how many dimensions are needed to adequately capture and describe an individual is itself difficult to answer. Personality traits alone can be represented by the five factors

5 *Quark and the Jaguar* is a book that explores how "complexity arises from simplicity." This perspective that complexity can be understood as the cumulative outcome of simple elements was perhaps the milestone most clearly established for us by complexity science in the 1990s. And under this milestone, agent-based modeling (ABM) stands as one of its constitutive cornerstone.

6 Strictly speaking, Gell-Mann was not the first scholar to articulate the concept of "agent-based." Rather, earlier predecessors who engaged with similar ideas employed alternative terminology before the label ABM came into use. For example, as will be discussed later, ecologists referred to it as "*individual-based*" (DeAngelis and Gross, 1992; Grimm and Railsback, 2005).

7 As he explains: "Discrete mathematics of the kind we have been discussing is often called rule-based. It is a natural kind of mathematics for digital computers, and it is often applied to the simulation of complex adaptive systems composed of many individual adaptive agents, each of which is itself a complex adaptive system.... In such cases, rule-based mathematics becomes agent-based mathematics, as used, for example, in TIERRA" (Ibid., p. 321). This provides one of the earliest uses of the phrase and places ABM in the lineage of modeling approaches for complex adaptive systems.

of personality psychology, the OCEAN model (Borghans et al., 2008). Cultural traits can be understood in terms of the six cultural dimensions proposed by the Dutch scholar Geert Hofstede (1928–2020; Hofstede, 2001).[8] To this we might add genetic information (DNA), epigenetic regulation (the ways in which environment shapes gene expression without altering DNA), family background, religious beliefs, ethnic lineage, educational attainment, developmental environment, health status, economic capacity, occupational role, and more. Taken together, it becomes evident that the dimensions needed to construct a "human profile" are by no means few; and within each of these dimensions, differences proliferate endlessly. This reality—that no two individuals are ever exactly alike—enriches the particularity that lies at the heart of the humanities (Harris, 2006).[9]

Therefore, when the EBM approach of treating "the forest as the trees, and the trees as the forest" proves untenable, a direct confrontation with complex heterogeneity becomes the only way forward. At this point, ABM—more "humanities-friendly" than EBM—naturally rises to prominence. In the words of sociologist James Coleman, "the internal analysis of system behavior is founded on a conception of human nature that resonates with the humanistic spirit." (Coleman, 1990, p.4) What Coleman calls the "*internal analysis of system behavior*" is precisely what we earlier described as the link from macro to micro and back to macro, or what has come to be known as *Coleman's Boat*. In this context, Gell-Mann's introduction of ABM can be interpreted as a critique of mainstream economics, which, in confronting Auyang's dilemma, tended to advance only superficially while ultimately avoiding engagement with the deeper challenges posed by heterogeneity.

In twentieth-century literature, one widely known novel is Milan Kundera's (1929–2023) *The Unbearable Lightness of Being* (Kundera, 1984). The novel reminds us that when life is reduced to a state of "lightness", a condition without weight, we may gain a temporary sense of freedom, but at the cost of losing a deeper connection with reality. Here, Kundera's metaphor is borrowed to frame the discussion above, suggesting that the significance of ABM in relation to EBM can be understood in terms of "*the unbearable lightness of science.*"

In the history of science, the elegance of EBM has long relied on a certain lightness, achieved by abstracting away individuality, context, and interaction. But as ecology, epidemiology, and the social sciences have shown, this lightness can no longer sustain the weight of real-world complexity. ABM emerged as a response, restoring individuality, heterogeneity, and locality to scientific explanation. Its value lies not in rejecting the elegance of equations, but in reminding us that without the weight of individuals, science risks losing its connection to reality.

5 ABM: the historical trajectory of the "return of weight"

As discussed above, the story of agent-based modeling is, in many ways, a story of the "return of weight." The rise of ABM marks a historical turn: it restores the weight of individuals, contexts, and interactions to the heart of scientific explanation. In the following, we will present several examples to demonstrate how what Milan Kundera metaphorically called the "unbearable lightness" (in *The Unbearable Lightness of Being*) finds resolution in ABM, and how ABM facilitates this "return of weight."

5.1 An illustration from ecology: the return of weight in the natural sciences

In the pursuit of ABM's potential, or in the urgency of its necessity, ecology was among the earliest disciplines to take the lead. Even before the rise of ABM, ecology already had its own classic equation-based models (EBM), most notably *the Lotka–Volterra system of equations* (Takeuchi, 1996). With the adoption of ABM, however, the ecological dynamics once represented by Lotka–Volterra can now be simulated and analyzed in new ways. Consider, for example, the two-species or three-species ABM models commonly used for the pedagogical purpose (sheep and wolves, or sheep, wolves, and grass). Simulation platforms such as NetLogo already provide standardized paradigms for research and instruction (Wilensky and Rand, 2015). Through NetLogo's visualization capabilities, we are no longer restricted to a single curve showing changes in population numbers; instead, we see sheep moving across the meadow, wolves chasing sheep, and the interactions of the entire population. Here, individuality and particularity are made directly visible.

Although in such paradigms sheep and wolves are usually still treated as homogeneous, additional data would allow us to introduce heterogeneity: different sheep with varying degrees of docility, or different wolves with varying levels of aggressiveness. The ABM framework makes it possible to restore such differences,

8 In psychology, the *Big Five Personality Traits* (also known as *the Five-Factor Model*) constitute a widely recognized framework for describing individual differences in personality. These five dimensions, commonly remembered by the acronym OCEAN, are Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (sometimes referred to as emotional stability). Complementing this individual-level framework, Geert Hofstede's *Cultural Dimensions Theory* is among the most frequently cited approaches in cross-cultural research. It identifies six key dimensions along which cultures can be compared: Power Distance, Individualism vs. Collectivism, Masculinity vs. Femininity, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation, and Indulgence vs. Restraint. Together, these frameworks provide complementary perspectives for modeling psychological and cultural variation in social simulation.

9 Judith Rich Harris (1938–2018) reminds us that individuality is not a single trait but the outcome of layered systems of interaction. The *relationship system* anchors us in bonds with specific others; *the socialization system* tunes us to group norms and cultural practices; and *the status system* positions us within hierarchies of recognition. These systems emerge sequentially, attachments at birth, group conformity in childhood, and status competition later in life, so that *human complexity unfolds over time*. For modeling purposes, this insight suggests that heterogeneity is not merely static variation across individuals, but *the product of dynamic processes of bonding, norm-following, and differentiation*. This layered view highlights why agent-based modeling is uniquely suited to capture the richness of human behavior.

thereby bringing "weight" back into the model.[10] Yet this form of "weight" still belongs largely to the natural sciences: it concerns the diversification of parameters and variables, transforming what were once homogeneous individuals into observable and quantifiable differences. This, at its best, can only be considered as a "return of parametric weight".

5.2 Social interaction models: the return of weight in the social sciences

In contrast to ecology, in the social sciences the rise of ABM carries an even deeper meaning. While ecology had already developed its classic equation-based models before the advent of ABM, the social sciences faced the more unavoidable challenge of addressing complex heterogeneity and individuality. For this reason, the "return of weight" that ABM brings resonates even more strongly in the social sciences.

James Sakoda (1916–2005) and Thomas Schelling (1921–2016) can be regarded as two pioneers who applied ABM in social sciences (Sakoda, 1971; Schelling, 1971).[11] To further grasp the spirit of ABM, it is worth revisiting the story of the Japanese American scholar James Sakoda. In 1971, Sakoda introduced the *Model of Social Interaction* (Sakoda, 1971), which, along with Thomas Schelling's contemporary *Segregation Model*, belongs to the class of so-called "*checkerboard models*." Yet the fates of the two models diverged sharply: in the very year that Schelling received the Nobel Prize (2005), Sakoda passed away quietly. Schelling's segregation model (Schelling, 1971) has since been studied and re-studied by countless followers, while Sakoda's models of social interaction and social structure were almost entirely neglected. The German sociologist Rainer Hegselmann expressed dismay at this disparity, devoting a lengthy article of nearly one hundred pages to analyzing the unequal recognition of the two scholars' contributions from the perspective of the sociology of science (Hegselmann, 2017). From the standpoint of ABM pedagogy, Sakoda's Model of Social Interaction demonstrates the distinctive features of ABM even more vividly than Schelling's segregation model.

To begin with, ABM is a highly visual modeling approach in which individuality and interaction are fully embedded within a concrete spatial framework. This spatiality becomes the pivot for stimulating thought, making ABM a relatively intuitive form of modeling that, at least in its early stages, does not demand extensive abstract reasoning. By way of analogy, ABM resembles *realist painting*, where the richness of detail and the concrete presence of figures guide the viewer's understanding. In contrast, equation-based modeling (EBM) is closer to *abstract painting*, where meaning must be distilled from symbolic forms and generalized patterns rather than directly perceived entities.

Sakoda's model exemplifies this spirit. His inspiration came from field research he conducted in a Japanese American relocation center (internment camp) during World War II (Sakoda, 1989a,b). From those observations, Sakoda quickly grasped the core of ABM—from human profiles to interactions. He began by distinguishing between "in-group" (Japanese Americans/European Americans) and "out-group" (European Americans/Japanese Americans) as the first axis of individuality. He then added a second axis: the behavioral rules governing how in-groups interact with themselves and with out-groups. In terms of interaction modes, Sakoda reduced the possibilities to three simplified emotional orientations: positive (favorable), negative (unfavorable), and neutral. With this parsimonious setup, dyadic interactions could be categorized into 81 possible relational patterns ($3 \times 3 \times 3 \times 3$). These 81 modes of social interaction were then used to simulate broader social structures, such as settlement distributions (Medina et al., 2017).

What is crucial here is that the "weight" restored by Sakoda was not merely the parametric weight of quantitative variation, but also the weight of *consciousness* and *relationships*. In Sakoda's model, the questions being asked are: Who am I? How do I perceive the other? How do "in-groups" and "out-groups" establish rules of interaction? These are already questions at the very heart of the social sciences—identity, emotion, relationship, and even prejudice. Thus, we can see that the "weight" brought back by ABM carries different layers across disciplines. In the natural sciences, the weight lies primarily in the quantitative differentiation of individuals: ABM allows us to move beyond averages to observe heterogeneous, concrete units (agents). In the social sciences, however, the weight rises to the qualitative dimension of consciousness and meaning. This represents a significant step forward in extending ABM toward the humanities.

5.3 Social contagion models: the return of weight in the social sciences

The above examples show us concrete breakthroughs of the unbearable lightness. When we examined James Sakoda's Model of Social Interaction, we encountered a deeper layer of "weight": consciousness, identity, and relationships. Yet Sakoda's framework remained bounded by its reliance on *ascribed attributes* such as skin color, ethnicity, social identity, features "given at birth" and fixed for the individual. Such models effectively reveal macro-level clustering and segregation (Medina et al., 2017), but the differences they capture are essentially *static*.

Robert Axelrod's (1997) *Model of the Dissemination of Culture* marked the next decisive step forward, shifting the focus from static difference to dynamic contagion. In his design, cultural attributes can change through interaction: the more similar two neighbors are, the more likely they are to interact; once they do, one adopts a cultural trait from the other. In this way, identity is not a fixed label but a mutable construct, continually shaped by

10 Just as the Lotka–Volterra system of equations in ecology has gradually come to be represented through ABM, the Kermack–McKendrick (SIR) equations in epidemiology (Daley and Gani, 1999) were likewise increasingly expressed through ABM during the 2000s and 2010s. The outbreak of COVID-19 directly triggered yet another surge in the use of ABM (Simler, 2020; Stevens, 2020).

11 The economist Guy Orcutt (1917–2006) proposed an approach akin to ABM known as *microsimulation* (Orcutt, 1957; Orcutt et al., 1961). Meanwhile, the economist Peter Albin (1934–2008), in his monograph (Albin, 1975), was the first to introduce *cellular automata*, originally used in artificial life research, into economics. Unfortunately, his work did not attract much attention from economists at the time.

influence and assimilation. This is the power of *acquired attributes*. It transforms the model from a portrait of frozen heterogeneity into a simulation of ongoing transformation. And it is precisely this dynamic contagion that makes Axelrod's work a landmark in the study of social epidemics. For what spreads is not only disease; ideas, beliefs, cultures, and narratives also propagate through contact and imitation. Axelrod translated this process into a set of simple yet powerful computational rules, showing how cultural diffusion could be formally modeled. Seen in this light, Axelrod's model represents not merely a technical advance but a new stage in the "return of weight"; no longer just the parametric differences of natural science, but the lived dynamism of culture itself—fluid, contagious, and profoundly human.

As early as 1841, Charles Mackay (1814–1889), in *Extraordinary Popular Delusions and the Madness of Crowds*, depicted how crowds fall into collective delusions and manias. Drawing on numerous historical episodes, Mackay illustrated how people think with the herd, go mad with the herd, and only slowly recover their reason afterward (Mackay, 2018). Yet Mackay did not provide any mechanism to explain how such collective delusions arise; what he offered were narratives of history rather than models of process. A century later, in 1956, economist Kenneth Boulding (1910–1983), in *The Image* (Boulding, 1956), interpreted human cognition and economic behavior as a kind of "chain reaction process." Although he, too, did not specify the underlying mechanism, Boulding suggested that the mathematical models of infectious disease, already well-developed by the 1950s, might shed light on it. The spread of disease, he argued, could serve as a paradigm for understanding more general processes of social contagion.

Thus, once the modeling of epidemics had begun to shift from equation-based to agent-based frameworks, it became natural to expect a corresponding development in the modeling of social contagion as well. Axelrod's Model of the *Dissemination of Culture* stands precisely in this lineage, providing a formal ABM expression of the very processes that Mackay could only narrate and Boulding could only analogize. Nearly thirty years earlier, Nicolas Rashevsky (1899–1972) had already envisioned that the equation-based models used in biological development might be extended to social and historical phenomena, encompassing dynamics of culture, imitation, transitions between equilibria, prejudice, geographical effects, trade, and the role of individuals in history (Rashevsky, 1968). It would take another three decades for this vision to be further enriched by the advent of ABM.

By 2019, Robert Shiller (2019) *Narrative Economics* brought the concept of "social contagion" directly into mainstream economic discussion. He illustrated how certain narratives, such as the panic of bank runs during the Great Depression, or the belief during the 2008 crisis that "housing prices can only go up", spread like viruses and in turn drove large-scale economic phenomena. In Shiller's framework, narratives themselves function as contagious units. More importantly, he operationalized them with digital textual resources: massive archives of newspapers, digitized books, and keyword time series. This allowed him to trace the popularity and turning points of specific narratives or expressions and compare them with economic variables. In this way, words, language, ideas, and stories were no longer confined to Boulding's qualitative descriptions; they could now be subjected to quantitative study. This was, in essence, a *digital humanities* approach, bringing the weight of language itself into measurable form.

Yet the "narrative contagion" that Shiller discusses in *Narrative Economics* is, in essence, mediated through words and language. By contrast, Axelrod's (1997) model of cultural dissemination operates with abstract symbols, i.e., features and trait, that stand in for cultural dimensions but are not themselves linguistic texts. As a result, while Axelrod's model can indeed function as a mechanism for social contagion, it does not extend to the finer task of capturing the contagion of narratives themselves. Its representational capacity therefore still falls short of engaging fully with the complexities of the humanities. This crucial limitation is something to which we shall return in the next section (Section 6).

In terms of the "return of weight," Axelrod's model points directly to a crucial insight, one that resonates with a much longer intellectual lineage. As early as Kurt Lewin's (1890–1947) pioneering experiments in social psychology, the focus was placed on how group dynamics shape the behavior of individuals, making him a central figure in founding experimental social psychology. Later, the Chicago School (George H. Mead, 1863–1931; Charles H. Cooley, 1864–1929; William I. Thomas, 1863–1947; Robert E. Park, 1864–1944) and Herbert Blumer's (1900–1987) articulation of *symbolic interactionism* further emphasized that social reality is not merely imposed from above but constructed through the everyday interactions, symbols, and languages that bind individuals to groups. The very tension that Axelrod formalized—individuals retaining a sense of self while simultaneously being molded, assimilated, or even transformed by cultural forces—was already foreshadowed in this tradition. What Axelrod's model accomplished was to translate these theoretical insights into a computational form: simple rules of interaction that generate macro-level cultural clustering and differentiation. In this sense, his work carries forward Lewin's and the symbolic interactionists' concern with the interplay of self and society into the domain of agent-based modeling, providing a formal demonstration of how micro-level encounters generate emergent collective patterns.

This represents a deeper level of "weight" than the parametric differences seen in ecology, or the "in-group/out-group" distinctions of Sakoda's model. It touches on a more profound dimension of humanistic complexity: how a person strives to maintain a sense of self within the group, yet may gradually lose that self in the cultural current, becoming an "other self." This is a "return of weight" in which the individual is assimilated and reshaped. At the same time, social contagion models reveal that individual differences must be understood within the swirling vortex of group influence, norms, and narratives.

6 Consilience: a new kind of heft

6.1 Literature and the next stage of social simulation

From the ecological models of the natural sciences to the interaction and cultural transmission models of the social sciences, we have seen how ABM has gradually brought "weight" back into science. From the weight of parametric heterogeneity, to the weight of consciousness and relationships, and finally to the weight of narratives and culture, ABM has indeed moved beyond the "unbearable lightness of science." Yet it is precisely at this juncture that the true challenge begins. If ABM is to continue advancing, it must answer a crucial question: *how can it become "heavier"?* The answer, as we have already suggested, lies in *turning back to the humanities*, to literature—and more specifically, to the novel—if we are willing to regard the novel itself as a form of social simulation.

The novel stages what economics cannot capture: the reality of a life that cannot be rehearsed. As Bookstaber (2017) observes, one of the fundamental difficulties of economics lies in its inability to represent "the self that continually changes with experience" and to grasp this radical uncertainty—an idea vividly illustrated in Herbert Simon's story *The Apple*, as discussed below (Sec. 6.4). What traditional models exclude, namely, the open-ended transformation of the self through unforeseen encounters, is precisely the essence of humanistic complexity. Put differently, the question of "who we are" cannot be reduced to fixed preferences or stable traits. This is also what novels so powerfully portray: they depict how individuals, in their unpredictable encounters with others and with their environments, are shaped, undone, or remade. To regard the novel as a form of social simulation is to acknowledge its capacity to model this very uncertainty and transformation. ABM, in turn, provides a methodological bridge: by allowing agents to embody, layer by layer, the "return of weight," ABM demonstrates the potential to approximate the humanistic realism of literature, thereby enabling forms of social simulation that embrace the radical uncertainty at the core of human life.

The novel's ability to simulate radical uncertainty and transformation is vividly exemplified in Milan Kundera's *The Unbearable Lightness of Being*. Kundera employs the metaphor of the "Planet of Inexperience" to remind us that human beings live only once, with no rehearsals or repetitions; life unfolds only in the midst of chance and uncertainty. Through the choices and transformations of his characters within this "one-time life," the novel simulates the existential condition of radical uncertainty. In this sense, the novel is not merely narrative but also a form of social simulation: it constructs a system in which characters, i.e., literary agents, interact under conditions of contingency and unpredictability, thereby revealing the complexity of human nature and social behavior. When we speak of the "unbearable lightness of science," the pursuit of a more meaningful weight requires us to ask: how will this weight ultimately encounter the depth of the humanities? Only at such a point of convergence can we fully experience a weight interwoven with the complexity of humanistic life.

Consider this trajectory: from *The Tale of Genji* (Murasaki Shikibu, Japan, early 11th century, ca. 1008), to *Dream of the Red Chamber* (Cao Xueqin, China, 18th century, first printed in 1791–1792; see Cao, 1973–1986), to *The Red and the Black* (Stendhal, France, 19th century, 1830), and finally to Dostoevsky's *The Brothers Karamazov* (Russia, late 19th century, completed in 1880). Of course, these are only a few among the many examples; yet they already demonstrate that the way novels construct and grapple with "human profiles" reaches a depth and complexity far beyond the current horizon of how ABM configures its "agents". What the novel presents is not merely the individual, but *the individuals within the individual*, namely, multiple selves, contradictory consciousness, and struggling souls. Through characters' dialogues, conflicts, and choices, novelists have long provided us with the deepest simulations of human complexity. By contrast, contemporary ABM models, while capable of capturing group dynamics, remain at a relatively shallow level and have not yet borne this degree of "weight." Therefore, only when ABM as *a scientific form of social simulation* ultimately converges with literature as *a humanistic form of social simulation* can we hope to construct *a new kind of heft*: a mode of social simulation that embodies both scientific rigor and the profound weight of the humanities.

6.2 Consilience of knowledge

And this convergence, the convergence of ABM and literature, echoes what Edward Wilson described in his 1998 book *Consilience: The Unity of Knowledge*. Wilson argued that the natural sciences, the humanities, and the social sciences should ultimately be integrated within a single rational framework. Yet his vision of consilience has often been criticized for bearing the imprint of *scientific imperialism*—that is, the privileging of science over the humanities, with the latter ultimately to be "constructed" or "explained" by the former (Gould, 2003; Slingerland and Collard, 2011).

In contrast, Stephen Jay Gould (1941–2002), in his final work published posthumously in 2003, *The Hedgehog, the Fox, and the Magister's Pox: Mending the Gap Between Science and the Humanities*, offered a more moderate and constructive perspective. Building on the principle of NOMA (*Non-Overlapping Magisteria*) that he had earlier articulated in *Rocks of Ages*, Gould (1999) emphasized that while science and the humanities differ in method, they should relate to one another on the basis of *equal regard*, rather than through a hierarchical or subordinate relationship. In the book, Gould draws on the fable of "the hedgehog and the fox": the hedgehog symbolizes disciplines focused on a single core truth, while the fox represents disciplines that respond flexibly to diverse experiences. These orientations should not exclude one another, but rather seek dialogue and complementarity within their differences. Gould reminds us in particular that if science and the humanities remain isolated, they cannot fully comprehend the human world; only by mutually recognizing each other's value can a genuine "consilience of knowledge" be achieved.

The dialogue between ABM and literature may thus be understood as a concrete enactment of Gould's vision of consilience, one grounded in mutual respect between science and the humanities. ABM has already been recognized as a central tool for unifying the social sciences under the banner of computational social science (Kohler and Gumerman, 2000; Gilbert, 2010). But its potential extends far beyond the social sciences. ABM can accommodate a wide spectrum of human characteristics, including inner contradictions, multiple selves, evolving identities, and intersubjectivity, endowing it with a unique expressive power that resonates deeply with literature and the humanities. In this sense, ABM may even provide a computational way to trace the footsteps of an individual in a complex world, generate biographies, or simulate the dynamics of a novel (Chen, 2021).

Chen (2021, pp. 149–155) has already demonstrated how ABM can be used to simulate "biographies." Drawing on Stephen Wolfram's Elementary Cellular Automata (Wolfram, 2002), Chen shows how a collection of artificial biographies, codes of life, can be simultaneously generated within simulated social interactions and time evolution. This approach highlights the generative power of ABM: it does not merely represent static individual attributes but produces life trajectories that unfold over time. Building on this, one may extend the vision further: if ABM can generate a multiplicity of artificial biographies, then it can also approximate the dynamics of novels, where multiple characters interact, evolve, and transform within unfolding cultural and social contexts.

In a parallel yet profoundly humanistic way, Haruki Murakami's *Underground: The Tokyo Gas Attack and the Japanese Psyche* (1997–1998) achieves through narrative what Chen's model enacts through computation: the simulation of lives unfolding and intersecting within a shared social field. In this work, Murakami (2001) reconstructs the 1995 Tokyo subway sarin attack not through abstract sociological analysis, but through a mosaic of biographical narratives, namely, interviews with both victims and perpetrators. Each testimony functions like an "agent," revealing how individual cognition, emotion, and circumstance interact within a complex social system. What emerges is a multi-agent portrait of contemporary Japan's collective psyche, haunted by alienation, conformity, and moral dislocation. Murakami's method, giving narrative life to data, and allowing individual trajectories to illuminate systemic pathologies, anticipates the spirit of agent-based modeling, though rendered through literary rather than computational means. His work thus offers a striking literary example of what might be called a *humanistic simulation*, demonstrating that fiction and testimony alike can simulate the interwoven dynamics of human experience and society, and exemplifying the very "return to weight" that humanistic complexity calls for.

6.3 ABM after the computational power revolution

Yet some twenty years ago, even when we attempted to place ABM's social simulations and literary/humanistic simulations within a framework of "equal regard," we still faced several fundamental technical obstacles. At the core of these challenges was the limitation of computational power. With constrained computing capacity, early ABM could only handle a narrow range of complexity. This limitation was especially evident in two areas: first, in the design of agent behavior, or what we might call *agent engineering* (Chen, 2008, 2021, 2023); and second, in the *modes of interaction among agents*, or *social interaction technologies*.

For agent engineering, Chen (2012) reviews three varieties of agents: simple programmed agents, autonomous agents, and human-like agents. This progression reflects a gradient of computational demand. Simple programmed agents operate on fixed rules, often the kind of "fast and frugal heuristics" (Gigerenzer, 2007), and thus require minimal computing power. Autonomous agents, by contrast, demand greater computational resources to support processes of learning and adaptation. Human-like agents, at the highest end of the spectrum, require far more computational capacity to capture psychological, cognitive, and cultural complexity, as well as the kinds of interactions that embody intersubjectivity and co-evolution. As one ascends this gradient, computational challenges intensify, and development becomes increasingly constrained. Not only have human-like agents remained limited in scope, but even autonomous agents have yet to attain a genuinely high degree of autonomy (Chen and Wang, 2011).

The limitations of computational power imposed not only a hierarchical bottleneck across different levels of agents but also deeply constrained the very ways in which agents could be conceived and engineered. Early ABM did not allow agents to be *freely constructed*; rather, they had to be designed and configured within specific theoretical frameworks, whether derived from the natural or social sciences. Following principles such as simplicity, minimal intelligence, entropy maximization, or generalized Darwinism, researchers relied on adaptive and evolutionary computational models ranging from reinforcement learning to genetic programming (Chen, 2023). This dependence made agent design restrictive and, at times, even clumsy.

Ideally, one might envision a large "agent database," populated with diverse human prototypes—each characterized by distinct qualities, dispositions, and behavioral styles—that could be randomly sampled to compose artificial societies. In such a framework, agents would no longer be confined to pre-specified theoretical molds; instead, they could, for instance, be *Dostoevskian,* acting in ways that reveal contradiction, passion, and irrational depth[12]; *Kafkaesque* (Kafka, 1998a,b), struggling to act meaningfully within incomprehensible systems of constraint[13]; *Camusian* (Camus, 1989, 1991), being aware of life's absurdity yet choosing to act with defiant freedom[14]; or *Proustian* (Proust, 1992–1993), shaped by involuntary memory and the recursive unfolding

12 At the heart of Fyodor Dostoevsky's (1821–1881) critique, especially in *Notes from Underground*, lies a revolt against the tyranny of rational optimization (Dostoevsky, 1994). In his view, if we model humans purely as utility maximizers, predictable "piano keys," or deterministic nodes in a perfect system, we eliminate what gives human existence its depth: contradiction, passion, guilt, rebellion, love, moral conflict, and the "heaviness" of choice (Morson and Schapiro, 2017).

13 Here, we are alluding to the recurring situation in Franz Kafka's (1883–1924) novels and stories—most famously *The Trial* (1925/1998) and *The Castle* (1926/1998). In these works, the protagonists (like Josef K. or K.) are trapped in vast, impersonal bureaucracies or legal systems whose rules are opaque, whose authority is unquestionable, and whose goals are never explained. The agents who follow rules; yet they don't know who made them or why.

14 Albert Camus's (1913-1960) central philosophical theme, as well manifested in his works, *The Myth of Sisyphus* (1942/1991) and *The Stranger* (1942/1989), is that human life is *absurd*—not in the sense of being ridiculous,

of time[15]. In other words, agents would behave like the individuals they instantiate, bringing customization and individuality into agent design. Yet realizing this vision requires massive data resources and major computational breakthroughs, conditions far beyond the reach of early ABM. Limited computing power prevented researchers from drawing upon the rich repertoire of human profiles found in social and historical archives—what we now call *big data*—as the foundation for agent modeling (Chen and Venkatachalam, 2017).

As to the modes of social interaction, although the idea of "talking" machines long predates the twenty-first century, early conversational AI lacked the depth and flexibility needed for integration into ABM. From Weizenbaum's (1966) ELIZA and Colby's (1972) PARRY to Winograd's (1972) SHRDLU, these systems could imitate speech through pattern matching or rule-based logic but could not truly interpret meaning, sustain context, or adapt dynamically to social environments. Their dialogue was syntactic rather than semantic—mechanical rather than cognitive. From the early 2000s onward, advances in computational linguistics and statistical natural language processing, such as *n-gram models* (Jelinek, 1997; Jurafsky and Martin, 2023) and *hidden Markov models* (Rabiner, 1989; Cutting et al., 1992), began to provide the linguistic and probabilistic scaffolding for machine understanding of text. Yet, despite their promise, these methods remained largely static, unable to generate the fluid, context-sensitive interactions required for ABM.

Without sufficient computing power or linguistic intelligence, early agents in ABM could not "listen to" or "speak" with each other; instead, agents could interact only through highly restricted channels, primarily numerical exchanges or the manipulation of a small set of predefined symbols. Consequently, agents could not communicate through natural language, nor could they process textual or visual information, not to mention multimodal communication. They were unable to approximate the richness of everyday interactions that characterize real social life, for instance, the fluid and nuanced exchanges that unfold on social media platforms.

Taken together, these two fundamental constraints—*agent engineering* and *interaction technologies*—prevented the development of agents capable of genuine language understanding and generation. Furthermore, although the notion of *autonomous agents* had long been central to ABM, a substantial gap persisted between theoretical aspiration and practical realization. Consequently, ABM at the time still struggled to capture the full complexity of the humanities: the mental and cognitive processes expressed through language and text, as well as the narrative depth and linguistic weight that define humanistic forms of social simulation.

but because there is a fundamental conflict between our deep human need for meaning and the world's indifference to that need.

15 For Marcel Proust (1871–1922), human identity is not linear or logical; instead, it is layered, recursive, and often inaccessible to reason. In his *In Search of Lost Time* (1913–1927/1992–1993), we are structured by memories that live beneath awareness, shaping our preferences, emotions, and choices long before reason intervenes. Each memory modifies the present, which in turn reshapes how the past is remembered, a process of recursive reconstruction. Thus, time doesn't flow forward uniformly: it loops, folds back, and expands through recollection.

The 2010s, however, marked a turning point, thanks to the computational revolution driven by the emergence of GPU (Graphics Processing Unit) and TPU (Tensor Processing Unit), the breakthroughs in deep learning and distributed representations of language, exemplified by *Word2Vec* (Mikolov et al., 2013a,b), introduced a form of representational continuity that allowed machines to capture semantic relationships between words. This representational breakthrough set the stage for a more dynamic engagement with meaning. By the 2020s, transformer architectures (Vaswani et al., 2017) and large language models (LLMs) such as GPT (Radford et al., 2018) and BERT (Devlin et al., 2018) had transformed this landscape entirely, enabling artificial agents that can not only "speak" but also reason, adapt, and evolve through interaction, thus making language-based ABM a realizable and profoundly humanistic enterprise.

Today, a new generation of ABM has already begun to use natural language as the basis of agent interaction, and large language models are poised to become the foundation of both agent engineering and social interaction technologies (Gao et al., 2023; Li et al., 2023; Park et al., 2023; Gao et al., 2024; Gürcan, 2024). In this new context, agents, or, in literary terms, protagonists, are no longer derived solely from theoretical assumptions; they can now be constructed directly from empirical reality.

Through an *Archetype Database for Agent Design*, characters from literary works can serve as prototypes for agents, with personality profiles, temperaments, dispositions, constraints, developmental trajectories, and interaction preferences all incorporated into their initial design. Such a database not only enriches the construction of agents within ABM but also facilitates the simulation of narrative and communication evolution. Agent design involves selecting one or more archetypes from the database as initial blueprints, and then developing the agent's individuality through learning, evolution, or interaction. This transformation points toward a future in which literary, historical, and social narratives or events can be dynamically explored, simulated, and reimagined through ABM. Rashevsky's mathematical dream, as we mentioned earlier (Rashevsky, 1968), now can be made possible by the convergence of computation, data, and humanistic imagination.

6.4 Yugo and autonomous agents 2.0

When Herbert Simon titled his autobiography *Models of My Life* (Simon, 1991/1996), he implicitly treated what a literary scholar might consider history or text as a *model*, something to be formalized and understood, rather than simply narrated. Yet the title itself invites a deeper reflection: if we were to apply the tools of modeling, such as model identification, missing-data treatment, or statistical estimation, to the trajectory of our own lives, we would quickly encounter all manner of difficulties, whether our models were parametric or nonparametric.

From the standpoint of evolutionary epistemology and evolutionary psychology, knowledge and behavior evolve much like living organisms. Thinkers from Jean Piaget (1896–1980) to Donald Campbell (1916–1996) and Karl Popper (1902–1994) framed the growth of knowledge as a process of variation, feedback, and selective retention—a Darwinian evolution of ideas. Later, evolutionary psychologists such as John Tooby (1952–2023), Leda Cosmides, and Steven Pinker extended this principle to cognition itself, portraying the human mind as an adaptive system shaped by environmental and social pressures. In both traditions, human beings are understood not as fixed entities but as self-modifying systems, continually discovering, revising, and adapting themselves through experience and interaction. Statistically speaking, our "life models" are therefore perpetually subject to over-identification, structural change, parameter instability, and robustness, the very challenges that arise when an evolving system attempts to model a world that is itself evolving. To live, in this sense, is to continually recalibrate the internal model of oneself and one's world under conditions of uncertainty and change.

Given these challenges, constructing models of agents or "models of lives" that can faithfully emulate human autonomy remains extraordinarily difficult. As stated earlier (Section 6.3), over the past few decades, most agent designs often build agents from scratch or grounding them in existing theories. Yet these theoretical foundations, though sound in isolation, remain fragmentary when situated in the context of lived experience. The long-standing aspiration for truly autonomous agents has therefore remained unfulfilled. The autonomy achieved so far has yet to produce behavior resembling Yugo's in Simon's story *The Apple* (Simon, 1991/1996).[16] Perhaps, then, what we lack in current agent engineering is not only a better algorithmic methodology but a way to endow artificial agents with this *dynamic interiority*—a mind that, like Yugo's, can outgrow its own model.

The advent of generative AI, particularly *multimodal generative AI* or *agentic AI*, urges us to reconsider what an *autonomous agent* might now mean. While both concepts represent advances in artificial intelligence, they address distinct dimensions of intelligence: *multimodal AI* emphasizes the ability to process and integrate multiple modalities—text, image, audio, and video—thus enabling a more holistic and human-like understanding of information; *agentic AI*, by contrast, stresses autonomy, goal-oriented behavior, and decision-making, allowing systems not only to perceive but also to plan and act with minimal human oversight. When combined, these two paradigms point toward a new synthesis—AI systems that both perceive the world through rich, multimodal input and act upon it through autonomous reasoning and adaptation.[17] For convenience, we may call this new generation *Autonomous Agents 2.0*. Following Judith Rich Harris's insight in *No Two Alike* (Harris, 2006), if *individuality* truly matters, then agents should not be confined to finite models with fixed parameters. Instead, an agent could be artificially generated by anchoring it to a real human biography—whether of a contemporary or a historical person. In this sense, the biography itself becomes the model of the artificial agent, allowing us, at last, to take Simon's title *literally*: *Models (Biographies) of a Man*.

These autonomous agents 2.0 would emulate a human counterpart across multiple dimensions, functioning as if *the Turing test* were applied to an individual's entire life rather than to language alone. By grounding the model in a person's biographical data, including the record of choices, preferences, and actions over time, the agent could be used to explore "what-if" scenarios that never occurred in reality. Adjusted for different stages of life and historical contexts, such simulations would allow us to infer how this person might have acted under alternative conditions.

How far and how meaningfully ABM can evolve in this direction remains to be seen. It will take time, experimentation, and reflection. Yet it is clear that the limitations of the first generation of autonomous agents have long been recognized. Either we continue to inhabit those limitations, or we dare to build differently. With the ongoing progress of AI, we believe the opportunity is before us, and early though primitive attempts already hint at a dawn (Gao et al., 2023; Li et al., 2023; Park et al., 2023; Gao et al., 2024; Gürcan, 2024).

7 Concluding remarks

In this article, we bring together agent-based modeling (ABM) and the humanities—not in the usual sense of asking how ABM might be applied to simulate aspects of the humanities, but in a more ambitious way: asking how ABM itself can be advanced, elevated, or even revolutionized by embracing humanistic complexity. To this end, we take an unconventional approach by illustrating the emergence of ABM from both the philosophy and the history of science, treating it as a response to their respective turns.

In particular, we endow these turns—those toward generative explanation and multi-level modeling—with symbolic and metaphorical meaning, borrowing Milan Kundera's notion of "the unbearable lightness" to characterize the integration of ABM and humanistic complexity as a "return to weight." Different kinds of "weight" are distinguished to clarify the progression of this returning voyage.

We then argue that this voyage can now be extended into a new kind of "heft," which was once beyond reach due to the technological limitations of hardware and software, but has become possible, thanks to the revolutions in ICT, AI, and computing power. While this voyage is far from complete, it already embodies a long-standing vision—namely, the consilience between

16 The story, originally inspired by Simon (1956) "*maze model*," transforms an abstract decision-theoretic construct into a metaphor of life. Its protagonist, Yugo, lives in a castle of countless rooms connected by one-way doors, endlessly searching for food, comfort, and meaning. At first, his actions follow simple satisficing rules: search, eat, rest, and repeat. Yet as time passes, Yugo develops preferences: a taste for particular food, an affection for certain paintings, and eventually, a longing he cannot satisfy. His life becomes burdened by conflicting desires, self-reflection, and the fatigue of endless choice. The allegory culminates when Yugo realizes that the forbidden "apple" is not merely an object of desire but a symbol of self-awareness: he has discovered, painfully, that to be human is to desire beyond necessity. Through *The Apple*, Simon gave flesh to bounded rationality, showing that genuine autonomy entails not merely adaptive calculation but the evolution of preference, meaning, and inner conflict.

17 The recent literature reflects this convergence of multimodal and agentic paradigms. For instance, Kar (2025) outlines the technical foundations for unifying language, vision, and action into coherent generative systems, while Caldwell (2025) provides a comprehensive framework for designing goal-driven, LLM-powered agents capable of autonomous reasoning and task execution.

science and the humanities—foreseen by early precursors such as Jonathan Swift (1667–1745) and C. P. Snow (1905–1980), and more systematically advanced by pioneers like Edward O. Wilson and Stephen Jay Gould.[18] What distinguishes our position from theirs is that we now stand at a new vantage point, able to enjoy a panoramic view they could only imagine but not yet attain.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Publisher's note

18 Jonathan Swift (1964) *The Battle of the Books* is one of the earliest satirical treatments of the conflict between the "Ancients" and the "Moderns," foreshadowing later debates over the relationship between humanistic learning and scientific progress. C. P. Snow (1959) *The Two Cultures and the Scientific Revolution* gave modern expression to this divide, diagnosing the growing gulf between literary intellectuals and natural scientists and calling for renewed dialogue between them.

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