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First author: Full name and affiliation; email address if corresponding author; any conflicts of interest
[Federico Bianchi, Department of Economics and Management, University of Brescia; federico.bianchi1@unimi.it]
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Abstract

This article looks at twenty years of applications of agent-based models (ABMs) in sociology and in particular their explanatory achievements and methodological insights. These applications have helped sociologists to examine agent interaction in social outcomes and have helped shift analyses away from structural and aggregate factors, to the role of agency. They have improved the realism of the micro behavioural foundations of sociological models, by complementing analytic modelling and game theory-inspired analyses. Secondly,

they have helped us to dissect the role of social structures in constraining individual behaviour more precisely than in variable-based sociology. Finally, simulation outcomes have given us a more dynamic view of the interplay between individual behaviour and social structures, thus promoting a more evolutionary and process based approach to social facts. Attention has shifted to applications of social norms, social influence and culture dynamics, across different disciplines such as behavioural sciences, complexity science, sociology and economics. We argue that these applications can help sociology to achieve more rigorous research standards, by promoting a modelling environment and providing tighter cross-disciplinary integration. Recently, certain methodological improvements towards model standardisation, replication and validation, have been achieved. As a result, the impact of these models in sociology is expected to grow even more in the future.

Introduction

Agent-based models (ABMs) are computer simulations of social interaction between heterogeneous agents (e.g., individuals, firms or states), embedded in social structures (e.g., social networks, spatial neighbourhoods or institutional scaffolds). These are built to observe and analyse the emergence of aggregate outcomes[1,2]. By manipulating behavioural or interaction model parameters, whether guided by empirical evidence or theory, micro-generative mechanisms can be explored that can account for macro scale system behaviour, that is an existing time series of aggregate data or certain stylized facts[3,4].

The origins of ABMs in sociology can be traced back to pioneering contributions by James S. Coleman and Raymond Boudon in the 1960s[5–7] and the publication of the first two volumes of *The Journal of Mathematical Sociology* in 1971. These included two important articles by James M. Sakoda and Thomas C. Schelling on segregation dynamics[8,9]. In these contributions, studying social outcomes by modelling agent behaviour and interaction in a computer was considered an alternative to the functionalistic, hyper-theoretical, macro-oriented social system theories that dominated sociology at that time.

However, it was only from the 1990s that ABM applications reached a critical mass. This development was thanks to the increasing computing power and the diffusion of the first open source ABM platforms. These platforms made explicitly individual behaviour models possible for the first time, without requiring excessive computing skills by the modeller. Initial sociological applications in the late 1990s covered the following areas: cooperation and social norms, diffusion, social influence, culture dynamics, residential ethnic segregation, political coalitions and collective opinions, to name but a few[10–14].

All these applications demonstrated that computational models can look at the dynamic nature of social facts better than most other social scientific methods. These include analytical equation-based models, used in standard economics and game theory, statistical regression models, used in macro-sociology and un-formalised, descriptive accounts, used in qualitative sociology. Due to mathematical restrictions, standard game theory and analytical modelling cannot account for the irreducible heterogeneity of social behaviour or look at out-of-equilibrium social dynamics, which are both intrinsic to the ABM approach. In this sense, the ABM approach is closer to behavioural game theory, which studies a variety of preferences and motivations through experiments, rather than standard rational choice theory, where homogeneous individual selfishness is assumed. While variable-based statistical models cannot easily deal with micro-generative processes, which are key to ABMs, descriptive, qualitative accounts cannot disentangle the effects of social networks and at the same time look at space, time and large scale social processes in the same way ABMs can.

By reviewing the first wave of ABMs in sociology in the 1990s, Macy and Willer[15] emphasised that ABMs are instrumental when the macro patterns of sociological interest are not the simple aggregation of individual attributes but the result of bottom-up processes at a relational level. Time has progressed since this influential review and advances have been made both in the extent and scope of ABM applications, in the number of sociological publications and in their methodological rigour. This article aims to report on these recent advances by considering examples, which looked at the importance of behavioural factors, cases that tested the effect of structural factors and models that pointed to the dynamic interplay of individual behaviour and social structures.

The article is organised as follows. The following paragraph looks at ABMs, which investigated social norms in cooperation and competition processes among individuals in stylised interaction contexts. This is one of the most vibrant ABM fields, where sociology and behavioural game theory have usefully interacted[16]. Their results showed the importance of considering the fundamental heterogeneity of social behaviour, the subtle nuances of individual rationality and the influence of social contexts in understanding aggregate behaviour. They also showed that sociological relevance increases when the interplay between individual behaviour and social networks is looked at in a more dynamic, co-evolutionary way.

The third paragraph looks at examples of ABMs, which investigated social influence mechanisms and the influence of certain structural constraints on social outcomes, such as residential segregation, stratification and collective opinions. These examples help us to understand that certain facets of the social structure might influence social connections among individuals. As a result they may have wider implications, including not only pressure towards social uniformity and convergence but also persistence of diversity in culture, norms or attitudes. At the same time, they help us to conceive the constructive role of the interplay of behavioural mechanisms and social structures in understanding the emergence of collective phenomena.

Finally, in the conclusion, we have summarised the key findings and discussed methodological implications.

Cooperation and social norms

Social life is rich with complex forms of cooperation between unrelated individuals that are channelled through social norms and institutions. Donating blood, being a witness at a trial or reviewing an article for a journal would not be possible if we were not able to overcome the temptation of self-interest to benefit others with our own effort. Given that natural and social selection tend to encourage competition, social norms and institutions must exist to provide a context for cooperation. Understanding in which contexts and for what reasons individuals can collectively generate social welfare despite self-interest, is one of the most important missions of social science.

We will look at the importance of certain social mechanisms in promoting cooperation in hostile environments, where there is a conflict between individual self-interest and group outcomes. Examples of these mechanisms could be direct and indirect reciprocity, reputation, social punishment, trust and social conventions. In this field, fruitful cross-fertilization already exists between behavioural game theory and ABM sociological analysis of social norms, with interesting extensions and modifications of standard game theory. Here, simulations were used to complement problems of analytic tractability of standard game theory as well as for exploring departures from its deductive, equilibrium-dominated framework.

Direct reciprocity

A key mechanism of social life is reciprocity, i.e., a form of conditional cooperation between related or unrelated individuals, which can be both direct or indirect[17]. Direct reciprocity means that two individuals are expected to cooperate if the probability of their future encounter exceeds the cost/benefit ratio of the altruistic act at an individual level. In this case, it is likely that certain aspects of social structure can have significant implications for cooperation as they influence the probability of encounters between two individuals, and so the type of behaviour they are exposed to[18].

It is widely acknowledged that the embeddedness of agents in a spatial structure, dramatically increases cooperation, as this determines a higher probability of encounter between correlated agents[19]. An interesting problem is to understand whether this can also happen in non-spatially related structures. A good ABM example of this is a study by Cohen, Riolo and Axelrod on an iterated Prisoner's dilemma[20] (see also Nowak and Sigmund[21]). They simulated a population of agents, who could cooperate or defect, reciprocate their opponent's behaviour (i.e., cooperating with cooperators and defecting with defectors) and imitate the behaviour of the highest fitted individual they encountered (with some noise), thus learning behavioural strategies from the social environment. They manipulated the initial network topology that connected agents to each other, by testing random encounters, spatial neighbourhoods, small-world networks and fixed networks. Results showed that even the sole persistence of interaction patterns from initially random encounters could make cooperation possible between selfish agents as it preserves favourable conditions for direct reciprocity, e.g., cooperators interacting more frequently among each other and receiving higher payoffs. This situation did not vary when agent behaviour was spatially correlated, i.e., spatial effects existed between neighbouring agents (see also Axelrod *et al.*[22]).

Although important, these examples neither assume a considerable influence of the social structure in shaping individual behaviour nor look at social mechanisms that exist to help individuals predict other agents' behaviour. If we consider that our life is mostly structured into social groups, it is probable that cooperation is influenced by group identity, so that we prefer to cooperate with in-group members and are less fair with outsiders. Coherently, in many circumstances, we tend to use tags or etiquettes (e.g., colour of skin, group dress style, or any other observational trait) to predict behaviour[23], which can even make us unconscious victims of stereotypes. The point here is that group identity or tags could substitute or magnify direct reciprocity.

Hales[24] built an evolutionary model which showed that cooperation could emerge in a mixed population of cooperators and defectors with randomly distributed tags playing one-shot Prisoner's Dilemma games with in-group members. Results showed that the formation of same-tag local clusters, in which cooperative groups eventually outperformed non-cooperative ones, could work even without assuming the memory of past experience, nor reciprocity-oriented strategies. Hammond and Axelrod[25,26] modelled a population of agents with different tags who could decide whether to cooperate or defect with in-group and out-group agents. Without building in-group favouritism in the model, simulations showed that the evolution of cooperation in a spatial structure could be sustained by the emergence of a dominant 'ethnocentric' strategy. That is, by which agents cooperated with in-group members and defected with outsiders, through the formation of local clusters of same-tag agents. Recently, Bausch[27] has questioned the tag-driven nature of Hammond and Axelrod's results, arguing that higher levels of cooperation might even be obtained by simply constraining interaction and reproduction to occur locally, without modelling different tags and preferential cooperation.

While these examples examined the importance of forward-looking strategies in repeated dyadic interaction, cooperation may also emerge from backward-looking strategies, with individuals capable of learning from past experience and adjusting their behaviour dynamically. Building on previous work on stochastic learning algorithms[28], Macy and Flache[29] built a series of models that included a variety of two-person cooperation dilemmas. Their results showed that adapting backward-looking agents could generate a self-reinforcing cooperative equilibrium but only within a narrow range of intermediate levels of the agents' aspiration. Mutual defection was more likely if agents had low or high aspiration levels as in these cases the context made defection worth-while, due to agent inertia (low aspiration) or individual dissatisfaction (high aspiration).

Please insert Table 1 here

The situation can change if agents could exploit forms of interpersonal commitment against the risk of being cheated. In this respect, following experimental research about commitment in dyadic exchange, Back and Flache[30] looked at the viability of committing – i.e., acting unconditionally cooperatively with some partners who have previously proved to be reliable – against a wide spectrum of other exchange strategies in a competitive environment. Results showed that commitment-based strategies are more viable than even tolerant versions of direct reciprocity, as they allow agents to create wider and more efficient exchange networks, while avoiding the vicious cycle of 'keeping the books balanced', which makes reciprocity-based strategies vulnerable to cascades of mutual retaliatory defection. It is worth noting that recent ABM studies have analysed the impact of reciprocity also in peer review and found a possible negative side of reciprocity when social sanctioning is absent or weak. Squazzoni and Gandelli[31] modelled the strategic behaviour of referees in a population of scientists called on to act as authors and referees during the peer review process in different competitive publication environments. Scenarios where referees were randomly reliable (i.e., providing more or less pertinent evaluation of author submissions' quality) were compared with others in which referees could strategically reciprocate past experience as authors by being more or less reliable with new authors. Their simulations showed that if referees' reciprocity is not inspired by fairness (contributing to scientific progress as a public good), but only by past publication or rejection when authors, peer review generates dramatic publication bias and allocates resources inefficiently (see Table 1; see also Thurner and Hanel[32]; Squazzoni and Gandelli[33]).

Indirect reciprocity and reputation

It is worth noting that individuals can also cooperate indirectly via third parties. In these cases, individuals could expect future benefits by cooperating with a counterpart from other partners, e.g., other group members, or by accessing or being subject to reputational information, e.g., cooperating with someone establishes good reputation that will be awarded by others[34].

Behavioural and evolutionary research has recently shown that the complex cooperation scaffolds that characterise social life seem to primarily depend on these complex forms of indirect reciprocity[17]. This has interesting sociological implications as social relationships pass from a dyadic to a triadic form and network effects are also included. This can help us to understand why social evolution involves the establishment of generalised forms of social exchange and large groups of unrelated individuals beyond direct reciprocity motives.

In this respect, many ABM studies have looked at the impact of reputation as a form of indirect reciprocity[35,36]. These studies emphasised two important functions of reputation: *learning* (accessing information about unknown partners via third parties which was not previously available and/or was too costly) and *social control* (monitoring and punishing norm violators through socially shared reputational signals)[37,38].

As regards to learning, Boero *et al.*[39] developed an ABM calibrated on behavioural data gathered from a lab experiment where subjects were asked to take investment decisions in a simulated financial market characterised by asymmetries of information and uncertainty. Subjects had different investment options, which were more or less risky and could receive/send information by/to others, so mimicking the formation and circulation of reputational information. Results showed, firstly, that subjects followed three types of behaviour, coherent with behavioural game theory findings, i.e., always cooperating with others by sharing reliable information, reciprocating reliable information only with reliable partners, cheating by always providing unreliable information to others. Secondly, results showed that socially sharing reputational information was beneficial for the exploration capabilities of agents in situations of uncertainty, independent of the quality of the information shared. Finally, they showed that reputation (social sharing of personal evaluation, even if potentially biased) was more effective than personal experience (formation of an opinion on the counterpart in direct interaction) in detecting reliable information partners and reducing the amount of false reputational information in the system.

In regards to social control, Conte and Paolucci[40] developed a model that also distinguished 'image' from 'reputation' and focused on social processes of reputation formation and transmission. They simulated a population of agents that followed heterogeneous behaviour, i.e., self-interest, altruism and norm compliance, in a social dilemma situation and manipulated simulation scenarios to add socially shared evaluation of other agents' behaviour. Results showed that, by allowing individuals to share the social cost of sanctioning against self-interested behaviour, reputation provided room for evolutionary stability of cooperation at levels hardly achievable by other mechanisms, e.g., direct reciprocity or cognitively sophisticated trustful partners' detection. Furthermore, they found that the circulation of false bad reputation tended to protect normative behaviour more than leniency (false good reputation) or silence. This work has influenced a large body of ABM research on reputation as a social control device for group behaviour[41–43].

Social punishment

Another form of indirect reciprocity is social punishment. Indeed, while reciprocating bad behaviour with a bad behaviour in some circumstances can create the conditions for cooperation, social life is full of examples of individuals bearing a personal cost for punishing wrongdoers, e.g., an individual reporting misbehaviour to the police to benefit a victim. This behaviour is called 'strong reciprocity' as it implies a direct reduction of payoffs imposed on the cheater at the expenses of the punisher without direct reciprocal benefits for the latter[44].

Empirically inspired by the case of mobile hunter-gatherer groups in the Late Pleistocene, Bowles and Gintis[45] have developed an ABM where a population of agents played an *n*-player Prisoner's Dilemma that mimicked cooperation problems in hunting, food gathering and common defence without any centralised institution. They explored a mixed population of egoists, cooperators and strong reciprocators. Due to the presence of self-interested agents, group benefits could be eroded by the fact that certain individuals could exploit the collaborative work of others without contributing themselves. They found that the robustness of cooperation depended on the co-existence of these behaviours at a group level and that strong reciprocators were functional in keeping the level of cheating under control in each group (see the shirking rate as a measure of resources lost by the group due to cheating in Figure 1). This was due to the fact that the higher the number of cooperators in a group without reciprocators, the higher the chance that the group disbanded due to high payoffs for shirking. This means that group structure may be the key to evolutionary social selection, even more than individual strategies (see also the test on the case of team collaboration in organisations by Carpenter *et al.*[46]). This is a relevant finding as it paves the way to consider whether social selection can be multi-level, working not only at a genetic-individual level but also at a social group level.

These findings were extended by Boyd, Gintis and Bowles[47] to situations of public punishment (i.e., the establishment of an institution, which monitors people's behaviour and punishes wrongdoers by exploiting economies of scale). Their results showed that also in the case of institutional punishment, the presence of a minimal fraction of strong reciprocators intrinsically motivated by social norms to support institutional punishment by paying fees and help social monitoring is instrumental to maintain cooperation over time.

Please insert Figure 1 here

More recently, Andrighetto *et al*.[48] built an interesting ABM based on experimental data in a public goods game similar to the previous examples, where punishment was combined with normative signalling. In this case, agents were called on to decide whether to cooperate by contributing to the public good or defect by exploiting other agents' contribution, punish defectors and send signals to others about the appropriate amount of contribution expected (i.e., the norm). As it is a focal point for what others expect as an appropriate contribution, signalling could affect individual preferences. Their simulations showed that punishment accompanied by norm signalling can ensure more robust cooperation at a lower cost for the group than when acting alone. They also showed that punishment is more effective when norm communication has already proved to be important for the perception of the norm by individuals. This socio-cognitive approach has been followed by other ABM studies to examine the cognitive counterpart of social norms and the importance of social contexts. These provide normative meaning and signals for individuals in typical social dilemmas, using an interesting mix of ABM, experimental and qualitative methods[49–52].

Trust

In many cases, we provide relevant information, time or money to others when we trust they will honour our help. However, in competitive environments and in situations of information asymmetry, distrust could prevail given that the potential benefit of interacting with others could be lower than the future cost of being cheated. On the other hand, when interaction is between strangers, with no previous experience of each other, a set of communication signals or tags might exist. These in turn could help individuals to convey and recognise the degree of trustworthiness of a potential partner and so risk cooperation. This is the case of taxi drivers and their relationships with customers, brilliantly documented by Gambetta and Hamill[53].

In order to look at the emergence of trust among strangers, Macy and Skvoretz[54] built a model in which agents could decide whether to engage or not in a Prisoner's Dilemma game by learning to display or mimic and recognise actual or fake signals of trustworthiness and eventually imitating successful strategies from others. They assumed that agents were embedded in a social network structure with neighbours and strangers through strong and weak ties respectively. Couples were randomly paired with a probability correlated with the social distance of agents. They tested the effect of different payoffs for not engaging in a risky exchange (i.e., an exit option) and the degree of the agents' network embeddedness. Results showed that cooperation between strangers could emerge in the long run, due to less costly exit payoffs that allowed agents to build clusters of trustful relationships locally that gradually diffused via weak ties, depending on the level of agent embeddedness.

Following experimental studies on cross-cultural differences on trust and commitment[55], Macy and Sato[56,57] tested the effect of spatial mobility on the emergence of trust and cooperation in a simulated population of learning agents. These played a repeated version of the Prisoner's Dilemma with an exit option and the possibility to choose to play with a neighbour or a stranger with different opportunity and transaction costs. Simulations found a curvilinear effect of mobility on trust. Indeed, the ability to detect trustworthy partners emerged only beyond moderate levels of mobility, which allowed agents to meet other partners. In case of higher levels of mobility, trust decreased because agents could not appropriately discriminate trust anymore.

These studies indicate that one of the main challenges for cooperation in trust situations is the capability of agents to detect trustworthy partners and build stable forms of interaction around them. In this respect, some studies have looked at partner selection in dynamic networks[58,59]. The idea here is that not only might individual behaviour vary from person to person and within the same person over time, but social networks are also constantly changing. This reflects new opportunities or constraints for a person when connected with another one. Behaviour and networks can change dynamically in a complex regime of possibilities/constraints that could have dramatic implications for macro behaviour.

Dynamic networks are also important factors in establishing trust. Bravo, Squazzoni and Boero[60] calibrated an ABM on experimental data on the behaviour of real subjects in a repeated trust game. They compared scenarios where agents were embedded in exogenously fixed networks (e.g., random, scale-free and small-world networks) and scenarios with endogenous networks, where agents could select their partners according to a simple happiness function. They found that cooperation dramatically increases in dynamic networks. Trustworthy agents tended to cluster around emerging cooperators, who had more ties and ensured higher profit to their respective partners. On the other hand, 'bad apples' tended to be isolated over time losing both profit and opportunities for exchange. Furthermore, while different initial network conditions did not affect this endogenous dynamics (see Figure 2), with more cooperative agents benefiting from an exponential growth of number of ties independently of the initial network constraints, the final network topology in case of initial random or regular networks, was different (see Figure 3).

Please insert Figure 2 here

Please insert Figure 3 here

These results were confirmed experimentally in an iterated Prisoner's Dilemma[61]. It was also confirmed in a model on a helping game where Chiang[62] allowed agents to use information of network characteristics (e.g., the structural attribute of the nodes) to strategize whether to cooperate or not. The co-evolution of behaviour and network created a crystallized configuration where cooperators had more ties and achieve higher profit so that cooperation outperformed defection over time.

This fact would indicate that social structure can endogenously generate role differentiation that may be relevant in generating conditions favourable to cooperation. For instance, Eguíluz *et al.*[63] simulated a spatial Prisoner's dilemma model where diverse social roles emerged from dynamic networks with '*leaders*', i.e., agents obtaining a large payoff, who were then imitated by many others, '*conformists*', that is unsatisfied cooperative agents, who keep cooperating and finally, '*exploiters*', i.e., defectors who have a larger payoff than the average obtained by cooperators. By endogenously converging towards a small-world topology, the network achieved a strong hierarchical structure in which the leaders played an essential role in sustaining cooperation. On the other hand, they found that once disruptions affecting leaders was introduced, a dynamic cascade was found, which propagated defection throughout the network.

Conventions

Social life is full of examples of social interaction where it is of mutual interest for individuals to converge towards a dominant behaviour, rather than compete on certain rewards at stake. We develop certain habits or conventions, e.g., language, monogamy vs. polygamy in marriage, a particular dress-code, that help us coordinate with each other more or less efficiently. Once established, these conventions can even be institutionally enforced, e.g., traffic rules. The challenge here is to understand the origins of these social artefacts, given that any coordination game may have multiple possible equilibria, no initial preferable options exist and outcomes are extremely sensitive to initial conditions, path dependence and increasing returns[64].

In order to understand this, Hodgson and Knudsen[65] modelled a population of agents randomly located in a 100 x 2 cell ring that had to decide whether to drive clockwise or counter-clockwise around a ring to avoid collision. Agents were characterised by a limited vision of space, inertia and a habituation level, i.e. the tendency to repeat past behaviour. Their simulations showed that the convergence of agents toward a right/left convention is higher when the level of habituation increases, independent of the error at the agent-level when estimating other agents' behaviour (see Figure 4). Furthermore, they confronted agents with different cognitive capabilities of monitoring the environment. They found that although habit had a positive effect on the emergence of conventions even for omniscient agents, the most striking influence was found when agents were boundedly rational, thus showing how habit can complement individuals' cognitive limitations in achieving coordination at a collective level.

Please insert Figure 4 here

Epstein[66] built a similar model to investigate the link between the strength of a convention and the cognitive costs that individuals have to pay to decide what to do. He simulated a population of agents in a ring, similar to the previous example, which had a heterogeneous sampling radius (i.e., space of vision). They could observe other agents' behaviour within their radius and could generalise global attributes by reducing or extending the search process around it. His simulations showed that two conventions could co-exist, with local conformity vs. global diversity patterns. However, this required considerable cognitive costs for intermediate agents, i.e., agents who continued to shift from one convention to another one. He also found that when a given convention equilibrium emerges, it feeds back to the agent-level by minimising cognitive decision costs, and therefore a macro-micro self-reinforcing path.

However, it is reasonable to presume that the emergence of conventions is also influenced by network effects, i.e., how agents are connected. Many studies have examined the influence of exogenous network structures on the diffusion of conventions[67]. It is probable that, while engaged in coordination problems, agents try to avoid those who behave differently and prefer relationships with agents similar to themselves. The consequences of these endogenous mechanisms of the formation of a social environment were explored by Buskens, Corten and Weesie[68] in a repeated coordination game model. Here, agents were called on to decide which opinion to endorse and their payoffs depended on the choices of other agents they were tied to. The authors examined the importance of initial network conditions on the emergence of conventions. They found that the density of the network had a crucial impact on the final conventions' equilibrium. The more segmented the network was, the higher the likelihood that two groups with different conventions emerged over time. This was due to the fact that certain agents preferred to have ties with agents similar to themselves, rather than adapting their behaviour to dissimilar ones.

The importance of these endogenous network formation mechanisms was also confirmed by Corten and Buskens[69]. Their findings from a repeated, multi-person coordination game model with network embeddedness were tested in a laboratory experiment. Here, subjects played a coordination game with payoffs depending on the choices of other neighbouring agents while they could create, maintain or break their ties depending on a certain cost. Results showed that agents were more efficient in terms of coordination, where the initial networks were less dense and they could endogenously adjust their networks.

Finally, it is worth noting that these results were also empirically tested on a longitudinal survey about alcohol use among adolescents in fourteen Dutch secondary schools, conducted in 2003 and 2004. Here, alcohol use was modelled as a risk dominant inefficient behaviour in a coordination game. Adolescents were motivated to align their behaviour with that of their friends to be approved socially[70]. While initial alcohol use propensity per class had a positive effect on average alcohol use at a later stage, the initial network density dramatically amplified this tendency[71].

Social influence

Individuals rarely make decisions in complete isolation of their social context[72]. The influence of social contexts on individual decisions is something that supporters of rational choice theory often tend to underestimate or conceive simply as information bias. However, in situations of uncertainty, the exposure to social signals from the behaviour of other people might influence our behaviour, as we presume that others know more than we do. At the same time, in group-life, we know that our behaviour is a signal for others who are observing and judging us. This is particularly important when the opinion of others can influence our access to important resources, e.g., economic benefits and social approval.

When the decisions of individuals are not independent but interdependent, choices do not simply aggregate at the macro level. This makes any micro-macro or macro-micro mapping potentially misleading if we do not consider the meso-level between individual choices and social outcomes. For instance, macro patterns can be the result of unintended consequences given that they do not reflect individual preferences but only interaction or propagation effects.

Segregation patterns

A classic example of the analysis of social interdependence is the famous Schelling's segregation model[9]. Here, a population of households of two groups, say black and white, was located in a two-dimensional space, characterised by regular neighbourhood structures, representing an idealised urban space. Households had a threshold preference about the group of their neighbours and could stay or move randomly towards new locations in case the number of similar neighbours was below the threshold. Results showed that even moderate preference for similar neighbours could tip a society into a segregated pattern. This was due to the interdependent nature of choices and their spatial and temporal effect on changing the context. Indeed, any household that reached its threshold and moved out of its neighbourhood reduced the number of similar neighbours in the original neighbourhood, leaving whoever was left closer to its threshold. Any movement of households also changed the receiving neighbourhood and indirectly also the neighbourhoods of the neighbourhoods, thus triggering a cascade of reactions towards an equilibrium of household distribution far from the original households' preferences (see Figure 5).

Please insert Figure 5 here

If we only looked at the individual level, we could predict macro segregation but with a more mixed residential distribution. If we only looked at the macro level, we should presume the segregational preferences of households, which was not the case. This abstract model allows us to understand that social context is typically a nexus of interdependence, e.g., the choice of A influences the choice of B, which influences the choice of C and subsequently that of A again. This makes it difficult for any linear micro-macro mapping (see also Sakoda[8]). This reminds us of the classic lessons of complex adaptive systems theory: even with simple agent interaction, there is always a possible gap between individual choices and aggregate processes so that looking only at individual levels, whether micro or macro, can lead us to draw illusionary conclusions[73].

Thanks to its simplicity and ability to be generalised, the Schelling's model has contributed to a prolific stream of ABM research. Certain authors have extended this original version by modifying important model parameters, e.g., preference thresholds, search for new locations, intentional household preferences toward integration, size of the neighbourhoods or spatial network topologies[12,74–78]. Gilbert[79] examined the influence of certain social attributes of neighbourhoods, such as crime rate, the neighbourhoods' perceived prestige and certain economic constraints, by providing households with more sophisticated cognitive processes of social environment's detection. Benito *et al*.[80] provided an experimental test of the Schelling's findings in a lab experiment. In all these cases, the original findings were corroborated and this contributed to make Schelling's model a general example of the unintended consequences of individual choices in social situations.

In a recent article, Bruch and Mare[81] started from empirical evidence that indicated that individuals tend to respond continuously to variations in the racial makeup of their neighbourhoods. They replicated the Schelling's model, but assumed that households could experience a small increase in desirability of their location for each given percentage increase in the proportion of similar households in their neighbourhood, so removing the threshold shape of households' preference. Their results showed that linear function preferences could soften residential segregation.

In response to Bruch and Mare's model, van de Rijt, Siegel and Macy[82] examined the rules that determined how households moved when they were unsatisfied. They showed that in a multicultural population with integrative preferences, threshold preferences at a micro level might help to prevent tipping, on condition that households made mistakes and moved to neighbourhoods that did not necessarily correspond to their preferences. This presumed that they did not have complete information about the real composition of the new targeted neighbourhood. They showed that once agents have a clear preference toward diversity, move to undesirable neighbourhoods or promptly react to the changes in their neighbourhood, segregation is likely to occur. On the contrary, once households have a clear preference toward ethnicity, react promptly to their neighbourhood's changes and rarely make mistakes in selecting their new neighbourhood, integration is more likely. This indicates that the shape of preferences does not have unequivocal implications, but rather that this depends on household preferences. It is worth noting that the importance of the contextual nature of preferences and the possible heterogeneous nature of neighbourhood composition was also found in an empirical calibration of Schelling's model in Israel[83,84].

More recently, Bruch[85] calibrated a segregation model by using empirical data on three cities in the U.S., the Panel Study of Income Dynamics and the 1980-2000 U.S. census data. She found that income inequality affects racial segregation. Given that higher between-group income inequality increases the salience of economic factors in residential mobility decisions, she found that high-income blacks live in whiter neighbourhoods than they would otherwise, whereas poorer blacks are racially and economically isolated. The focal mechanism is called 'offsetting': under sufficiently high levels of within-race income heterogeneity, increasing between-race income inequality can have opposite effects at the high and low ends of the income distribution. Whether these offsetting processes cause a net increase or decrease in segregation depends on the relative size of the black population, the salience of racial versus economic factors in residential mobility decisions, and the shape of the income distribution.

Finally, it is worth noting that Schelling's findings have also been extended into policy and health fields. For instance, Auchincloss *et al*.[86] showed that residential segregation might play a role in determining the diffusion of obesity and related illnesses in low-income families. By adding food price and preferences and locating stores across the neighbourhoods in the model, they showed that *ceteris paribus*, residential segregation alone could increase income differential in diet, independent of the low-income households' food preferences. Negative implications of residential segregation were also found in public goods provision[87], income distribution[88] and quality of schools and labour market[89].

Cultural and opinion dynamics

Although social influence would lead us to expect a dominant tendency towards convergence in collective behaviour, social systems often display persistent dynamics of cultural and opinion diversity. Minority beliefs or opinions tend to persist over time, independent of any social force pushing them towards uniformity. This is especially relevant when we observe the persistence of collective misbeliefs and discriminatory stereotypes in certain societies or the impact of extremist groups in politics.

Influenced by Latané's social psychological theory of social impact[90], Nowak, Szamrej and Latané[91] modelled a population of agents in a lattice with randomly assigned binary values of an opinion variable and heterogeneous levels of persuasiveness and supportiveness. These levels were defined respectively as the ability to make out-group agents change their opinion and in-group agents to resist outsiders' persuasiveness. Agents changed their opinion value according to the relative impact of total persuasiveness or supportiveness exerted on them by other agents, weighted by their distance from the agent within the matrix. Simulations showed that, besides the emergence of a dominant opinion, the formation of strong local minority clusters prevented in-group agents being influenced by the majority. This determined the emergence of a polarized stable equilibrium, with local convergence and global polarization of cultural traits, due to the high sensitivity of persuasiveness and supportiveness to structural embeddedness factors.

This avenue was further explored by Axelrod[13], who built a more sophisticated model to test the effects of structural embeddedness, cultural heterogeneity and interpersonal influence on convergence and polarization outcomes. Adaptive agents were modelled with heterogeneous cultural characteristics, defined as a combination of a fixed number of cultural features (e.g., language, religion, etc.), each taking *n* possible trait values (e.g., English, German, Italian; Christian, Muslim, etc.). Agents interacted with neighbours with a probability dependent on the number of identical cultural features they shared. A mechanism of interpersonal influence was added to align one randomly selected dissimilar cultural feature of an agent to that of the partner, after interaction. The author manipulated certain parameters of cultural heterogeneity (number of features and number of traits) and structural embeddedness (interaction range and environment size). Confirming previous studies, Axelrod's simulations showed that global convergence towards a single culture did not occur, despite interpersonal influence mechanism. Moreover, they showed that the number of emergent cultural groups positively correlated with the number of cultural features and negatively correlated with the interaction range. This was because large-distance interaction amplified the effect of interpersonal influence from the local to the global scale. However, cultural diversity was unexpectedly found to negatively correlate with both the number of possible traits and the environment size. More recently, Klemm *et al.*[92] found that cultural homogeneity could eventually emerge due to low rates of random cultural perturbations, which caused the collapse of boundaries between otherwise dissimilar neighbours. Moreover, by looking at the co-evolution of network structure and agents' partner selection, Centola *et al.*[93] identified a certain size-dependent perturbation parameter region for which interpersonal influence and homophily prevented the evolution of the system into monoculture or unstable global cultural diversity. This in turn generated a stable polarized global equilibrium.

However, the unrealistic narrowness of such parameter region was pointed out by Flache and Macy[94], who found a stabilising mechanism for the emergence of a bipolarized global equilibrium. They questioned the assumption of the dyadic character of social influence in favour of a multilateral model of that mechanism[95]. Their results showed that multilateral interaction could be a more robust mechanism for the persistence of cultural diversity, especially in large populations, as local clusters could better resist deviant agent influence under conditions of perturbation, and eventually prevent it from spreading globally.

It is worth considering that the local convergence and global diversity pattern can also be generated when homophily or social influence are not expected to play a crucial role. Combining standard game theory and ABMs, Bednar and Page[96] showed that certain structural characteristics of cultural dynamics might be generated by purposive agents playing multiple games without reacting to evolutionary pressures. Similarly, Bednar *et al*.[97] showed that a certain level of diversity could persist within local cultural clusters. By assuming that culturally heterogeneous agents, besides facing social pressure to conformity, also strive for internal consistency among their own different features, they showed that global convergence could emerge in the long run, yet allowed for an intermediate phase in which cultural heterogeneity persisted.

Social influence is also important for the formation and diffusion of political opinions, including the rise and propagation of minority political positions. By extending previous studies on opinion dynamics[98,99], Deffuant *et al*.[100] built a model in which a continuous opinion variable x ($-1 < x < 1$) was distributed within a population of adaptive agents. In this way, moderate and extreme positions on a political issue could be contemplated. Agents were also equipped with an uncertainty value, negatively correlated with the level of the agents' political radicalism, following the assumption that radicals are more confident of their own opinions. Both opinion and uncertainty could change over time through interaction, so that agents randomly coupled and influenced each other if their opinion distance was lower than a threshold, eventually leading to converging opinions. The agents' influence negatively depended on their level of uncertainty. By manipulating the uncertainty distribution and the proportion of radicals in the population, they showed that for low levels of uncertainty, the influence of radicals was effective only on a small proportion of closer agents, eventually leading to convergence around moderate levels. However, for high uncertainty levels, radicals prevailed, causing concentration of opinion distribution either on a single extreme or on both (bipolarization).

By adding a social network structure to the previous model, Amblard and Deffuant[101] showed that extremists could exploit low connected networks better, as they could spread in local clusters and co-exist with the rest of the population. On the other hand, when connectivity increased around a critical value, the extremists were confined to peripheral regions by core moderate agents. Furthermore, Deffuant[102] compared different formal models of opinion and uncertainty across three network structures, pointing out that extreme convergence was possible in certain network configurations which favoured the isolation of clusters of moderates and permitted radicals to influence other agents without being influenced in turn.

Polarization can be further influenced by the fact that in social life partner selection might be driven by xenophobia[103]. This implies that negative interpersonal influence could even exacerbate this tendency. In order to consider this, Macy *et al*.[104] developed a model of adaptive agents with binary cultural states, which were embedded in a full-connected network of weighted undirected ties. Weights, w ($-1 < w < 1$), incorporated information about the strength and the valence (positive or negative) of the influence between agents in dyadic interaction, were randomly distributed among the ties and could evolve according to changes in the number of similar traits. By manipulating decision-making flexibility and number of cultural states, results showed that a bifurcating network equilibrium emerged. A stable outcome towards homogeneity would not occur, unless only positive valence of partner selection and social influence were assumed. In a development of this model, Flache and Macy[105] tested the effect of the bridging role of «long-range ties»[106] in fostering cultural convergence, by allowing agents to create dynamic networks within different exogenous network structures. Results showed that long-range ties did generate cultural homogeneity but only when interaction was limited to positive selection and influence. On the contrary, in cases of bivalent influence, long-range ties induced a polarized equilibrium.

By looking at U.S. American public opinion, Baldassarri and Bearman[107] investigated the bivalent nature of partner selection and social influence mechanisms to explain the mismatch between perceived and actual polarization both at a local and global level. They modelled a population of agents with heterogeneous opinions about multiple political issues, attaching different levels of interest to each of them, whose sign represented the opinion on them (either positive or negative). Interaction partners were selected with a probability inversely depending on the perceived ideological distance between the agents. Moreover, interaction directly depended on the absolute value of the interest level that agents attached to different issues. Agents then interacted by focusing only on the issue in which they were interested in the most and could then update their opinions. Simulation results showed that bivalent selection and influence across multiple issues caused clustered polarization in the emergent interaction structure. However, the overall distribution across multiple issues was not polarized, except for highly salient take-off issues. This can explain why individuals' perception of opinion homogeneity in local interpersonal networks emerges from gradual segregation of interaction partners around take-off political issues, despite the fact that individuals still had heterogeneous opinions about other issues.

Furthermore, it is probable that individualization mechanisms besides homophily-driven social influence can affect collective dynamics, i.e., the tendency of certain individuals to increase their own 'uniqueness' when their group starts to become overcrowded[108]. For instance, Mäs, Flache and Helbing[109] tested the effect of individualization on cultural convergence by building a simple model with mechanisms of choice homophily and non-negative social influence. By assuming a noise parameter that imposed agents' changes of opinion depending on other similar agents in the group, they showed that a phase of stable clusters with diversity between and consensus within tended to emerge. In this same vein, Mäs and Flache[110] developed and experimentally tested a model of homophily and social influence in which agents interacted through the exchange of arguments instead of adjusting to each other's opinions. Their results showed that interpersonal communication generated a bipolarized equilibrium but only for high levels of choice homophily.

This approach has also been applied to diffusion dynamics of innovation. Deffuant, Huet and Amblard[111] extended the continuous opinion dynamic models by simulating agents who held dynamic opinion values about the impact of a particular innovation on society – i.e., its social value. Agents could collect and share information for the assessment of expected individual payoff, only when the social value was considered to be high enough. Their results suggested that under these conditions, innovations with overall high social value but low expected payoffs were more likely to succeed than innovations with low social value but higher individual benefits. Moreover, diffusion dynamics are significantly influenced by at least a minority of radical innovators.

More recently, Van Eck, Jager & Leeflang[112] developed an empirically-grounded ABM to study the effects of opinion leaders on the diffusion of innovation via normative and informational influence. The basic concept was that agents could adopt innovation either stemming from social pressure or from social information about quality. A sample of free online game consumers was used to calibrate the behaviour and position of opinion leaders. Opinion leaders were situated in central positions within the network. They were more prone to adopt innovations, could assess the quality of a product better and were also less permeable to normative influence. Comparing network configurations with and without opinion leaders, the authors found a significant effect of opinion leaders on the rapid spread of diffusion. This was because they could spread positive information about the quality of the products and were less likely to be affected by the normative influence exerted by more conservative agents.

Collective behaviour

Our decision to join a social movement or spread a cultural fad depends heavily on the effects of social influence. This is because we are often influenced by observing other people's behaviour before deciding what to do. It is often hard to understand empirically how certain collective behaviour are produced when individuals are subjected to social influence without analysing the effect of social structural factors, such as complex network configurations.

In this field, a seminal model was published by Granovetter[113], who analysed the dynamics of a type of collective behaviour, such as a riot, by simulating agents deciding whether to join it depending on the decisions of other agents. Agents were modelled to make a binary choice, according to an expected benefit dependent on a heterogeneously distributed threshold value of how many agents were already participating. In a simulation scenario, he added the impact of previous decisions of relevant agents connected to the individual. His results showed that whenever network externalities are added, collective behaviour becomes extremely dependent on non-linear dynamics, which make any prediction of macro behaviour on single individual preferences very hard to make.

Threshold models of collective behaviour have also been used to analyse innovation diffusion dynamics. By integrating Granovetter's classic model with a network structural component, Abrahamson and Rosenknopf[114,115] looked at the differences in bandwagon effects due to certain network communication properties. They found that bandwagon effects in innovation diffusion within a network also depend on particular structural characteristics of nodes that bridge core and peripheral components and the permeability of their boundaries. Furthermore, by weighting social influence with exogenously distributed opinions about the reputation of innovations, they showed that bandwagon effects could override information about their unprofitability, eventually leading agents to converge on inefficient practices.

Hedström[116] relaxed Granovetter's original assumption of homogeneity of interpersonal influence and added the more realistic dimension of spatial embeddedness to this model. He assumed that agents were more influenced by spatially closer connections. He used data on the extraordinarily rapid diffusion of trade union organizations in Sweden between 1890 and 1940 to test this model. Simulations showed that the spatial-based structures of social contacts could explain the empirically observed behaviour.

A more complex model was elaborated by Kim and Bearman[117] to explain the participation to social movements. Their model showed that there was no need to assume agents' irrationality to explain why individuals voluntarily engaged in collective action even when this was risky or costly. They simulated the interaction between agents with different interest levels in providing a public good – from whose benefits no agents could be excluded – and the different amounts of resources to produce it, which shaped a dynamic network. Agents decided whether or not to contribute according to the expected marginal benefit, which they calculated upon their interests, the cost of participation and the amount of resources they possessed. However, the agents' interest in the good varied either upward or downward depending on whether their ties had previously contributed or defected. By manipulating various structural parameters, simulations showed that a critical mass of highly interested agents situated in central network positions, even if guided by self-interest, could create a local dense cluster, which eventually neutralised the influence of defecting agents. In particular, network density was more decisive to achieve this critical mass than high concentration of resources.

Chwe[118] proposed a model in which strategic agents chose to participate in a collective action depending on the expected number of participants among their neighbours. Consequently, expectations of neighbours' participation depended in turn on expectations of neighbours of neighbours' participation and so on. The agents were assigned a fixed number of partners for the whole simulation cycle. By examining the effect of network transitivity on social influence, results showed that transitivity was particularly effective in triggering bandwagon effects among agents with low thresholds, as they could get information from locally small and yet dense clusters. For agents with high thresholds, however, weak ties were especially important as they transmitted information about a larger amount of agents.

Social inequality

It is probable that social influence is responsible for a variety of dysfunctional collective patterns typically observed in macro quantitative sociology. These include inequality in educational opportunities, social stratification, employment traps in the labour market, and the co-evolution of social and workplace segregation[119].

For instance, by looking at the labour market, Hedström and Åberg[120] built an empirically calibrated ABM to examine how social influence mechanisms can explain aggregate youth unemployment rates. Their hypothesis was that levels of unemployment among neighbourhood peers had an effect on youth unemployment by lowering their expectations of finding a job, reducing the psychological costs of being unemployed and preventing outsiders accessing insider information about job opportunities. Large-scale observational data on youth unemployment in Stockholm between 1993-1999 was used to calibrate the socio-demographic characteristics of individuals and the structural features of the neighbourhood network clusters. Transition probabilities of leaving unemployment were also estimated through maximum-likelihood statistical modelling. The author assumed that agents decided to leave unemployment according to their own socio-demographic characteristics, the unemployment rate in their neighbourhood, and the tightness of the job market. Simulations showed that the combination of social influence and agents' educational level provided the most striking effect on the population's rising unemployment rate. Furthermore, the effect of social influence was comparably higher than that exerted by the agents' educational level *per se*.

When looking at social stratification, it is likely that there is a persisting effect of social origin on educational attainment, which has traditionally been explained through rational choice approaches[121]. Recently, Manzo[122] proposed an ABM to improve the realism of standard rational choice models by introducing a social influence mechanism within friendship networks. Agents were assigned into four groups, representing background social classes. They were then embedded in a small-world network and took decisions about transitions from an educational level to the next one. These decisions were based on the evaluation of their own ability, the perceived cost/benefit ratio, their probability of success in function of their ability and the effect of the overall social influence exerted by others with whom they were tied. Simulation findings were tested against observational data about the French stratification of educational choices across social origin in 2003. Results showed that only by considering a social influence mechanism could the model generate outcomes sufficiently close to the empirical data.

Another interesting field includes the study of the social influence effects on the reproduction of status. Analytical theories explain the emergence of status hierarchies as the result of a self-reinforcing process driven by the exchange of deference-conferring gestures (i.e., the attribution of a perceived quality evaluation). This amplifies already existing qualitative differences between individuals[123]. Recently, Manzo and Baldassarri[124] tested the potential inequality-driving effect of social influence on status attribution mechanisms, by hypothesizing a counteracting effect of reciprocity in the exchange of deference-conferring gestures. They modelled a population of agents with heterogeneously distributed 'quality' values, assessing each other's quality and exchanging deference gestures. In addition, they could become biased by other agents' behaviour. The agents interacted on the basis of status homophily, selecting partners within an acceptable range of status dissimilarity (corrected by a heterogeneously distributed 'heterophily' constant). They also assessed partners' quality, by considering the partner's previously acquired status, their own tendency to rely on social influence and a noise value. Subsequently, the agents transferred a deference value to their interaction partners, which was equal to the partner's perceived quality, unless the evaluating agent had previously received less deference than expected from the partner. In the latter case, according to a heterogeneously distributed parameter for sensitivity to reciprocity, the evaluating agent reciprocated the partner's previous unfair behaviour by exchanging less deference. Status values were then calculated for each agent as the average deference received. The simulation results suggested that the interaction between the cumulative effects driven by social influence and the counterbalancing effect of conditional deference exchange, was sufficient to generate status hierarchies, qualitatively similar to those observed in empirical research, that is, the increasing gap between actual quality and status asymmetry. Furthermore, if low-status agents were more prone to have mixed interaction with similar and dissimilar agents rather than high-status agents, outcomes tended towards a 'winner-takes-all' status hierarchy.

Finally, Gabbriellini[125] built an empirically-tested model of the emergence of status hierarchies in task-oriented groups as the effect of a network of precedence ties[126]. He modelled the interaction within a disconnected network of agents, who could participate in a discussion with other members by addressing precedence claims in the hierarchy to all others (i.e., asking everyone to accomplish a task). Agents' participation depended log-linearly on the expected consequences of their claim. Permanent precedence ties were established with a probability, which partially depended on comparing agents' external status values, which were activated according to a probabilistic value. He collected empirical data on communication in an online task-oriented discussion forum of a role-playing game community. His simulations showed that highly linear status hierarchies, – similar to those observed – were due to the higher participation of agents in communication and the deference generated by mutual observation of external status.

ABM platforms for sociologists

Various software platforms are available for sociologists to build ABMs. The main ones are open-source and have been constantly developed by large user communities. They provide researchers with specific developing tools, graphic user interface, and libraries to implement various programming languages. **Swarm** was the forefather of all ABM platforms. It was developed in the early 1990s by an interdisciplinary team at the Santa Fe Institute. It has implementations in Objective C and Java (http://www.swarm.org). Another popular platform is **Repast** (http://repast.sourceforge.net/), which was developed by a team at the University of Chicago and has implementations in various object-oriented languages, e.g., Java, C++, Microsoft .NET and Python. It also allows GIS programming and it is easy to create sophisticated visualizations. It is well-documented and used by a growing user community. Models with Java can also be programmed with **MASON** (http://cs.gmu.edu/~eclab/projects/mason/), which was developed by a team from George Mason University. Finally, developed by a team at Northwestern University (Chicago, U.S.A.), **NetLogo**[127] (https://ccl.northwestern.edu/netlogo/) is currently the most famous ABM platform, although it is not based on an object-oriented programming language. It provides an integrated modelling environment based on its own programming language, a dialect of Logo (an educational programming language, originally designed to train youngsters). NetLogo can be ideally considered as the best solution to start learning ABMs as it is user-friendly, well-documented and has a large set of ready-to-use models, including some of the classic studies mentioned in this article. It is also the most commonly used platform for educational purposes.

Discussion and conclusions

This article presents a number of sociologically relevant ABM studies that explain complex social outcomes as effects of agent interaction. Table 2 summarises the most important contributions and provides a systematic overview on their main explanatory achievements. These cases combine abstract models, which look at general mechanisms of social phenomena, e.g., cooperation and social norms. It also looks at middle-range models, where specific social puzzles are analysed, such as youth unemployment and education. Although the prevalence is for theoretical approaches, some empirical applications of these models also exist, where important behavioural or structural model parameters have been calibrated with available or *ad-hoc* generated empirical data. In these cases, these models have been used to complement empirical data by manipulating certain parameters (e.g., complex social networks) that would be difficult to observe empirically[60], or used to generate empirically tested hypotheses[69]. In other cases, models have been used to reproduce certain macro empirical regularity by a given theory[122,125].

Although most sociologists shrink from abstract, formalised theories, these examples show that abstraction can have a crucial role for theory building even in sociology when it is guided by modelling. On the other hand, empirically grounded studies are fundamental to explain well-studied sociological puzzles and stimulate cross-methodological approaches with mutual benefits between, for examples, standard quantitative sociology and ABMs. Furthermore, this type of study is pivotal in persuading traditional sociologists about the advantages of this approach.

At a substantive level, these examples show that exploring the fundamental heterogeneity of individual behaviour is of paramount importance to understand the emergence of social patterns. Cross-fertilization between experimental and computational research is a useful process. It shows us that by conflating the concept of rationality with that of self-interest, as in standard game theory and economics, we cannot account for the subtle social nuances that characterise individual behaviour in social contexts. In this respect, Gintis[128] suggested that we questioned the aprioristic assumption of common knowledge that lies behind standard game theory. If we assume that individuals are rational, self-interested as they perceive their counterparts, game equilibria of any social or economic exchange can be predicted. The problem here is that experimental research has repeatedly found that social outcomes are better explained if we recognize that people develop an 'epistemic knowledge' within the game based on implicit 'shared mind' efforts. Culture, social norms and learning as social scaffolds for individual rationality makes a wider set of behaviour 'rationalisable', which would otherwise be far from standard self-interest (see also neuro-scientific research on the positive role of emotions[129]).

Behavioural game theory could help to explore departures from standard rational choice models. Furthermore, they can be used to understand social norms in well controlled experimental scenarios, relevant for sociological research. By concentrating on interaction situations where self-interest is expected to prevail, we can understand the genesis of social norms, their dynamics, in terms of fragility or robustness and the factors that could condition their evolution. This is impossible if we assume that individuals have no individual autonomy (also that of being self-interested) and passively internalise norms by culture, education or social conformism, as in many standard sociological accounts.

Interestingly, most ABM studies mainly look at the self-organisation of social groups around social norms and should not be seen as a naive exercise. No one believes that institutions and top-down influences simply do not exist. At the same time, the ABM approach is not a bottom-up 'market' ideology. By focussing on micro-macro aspects, ABM studies can offer relevant insights on how groups and communities can coordinate and collaborate in our world. This is more and more fragmented into cultures, contexts and domains and in constant evolution and change. This is to say, the ABM approach is also sociologically timely and can contribute to understanding social change.

These ABM studies show that, if we consider society as an evolutionary system in constant change and adaptation, the co-existence of different behaviours and norms over time is instrumental to promote and maintain social order. This means that institutional policies, which typically assume that individuals are self-interested, end up eliciting self-interest in people. This situation could actually worsen the long-term sustainability of social systems for the following reasons: Firstly, they do not nurture diversity and heterogeneity of behaviour and secondly, they can crowd out pre-existing social norms and intrinsic motivations[130]. In these cases, ABM studies could be used to understand when incentives, regulations and external institutional design can work, when social norms are beneficial and when institutions and social norms can work in synergy.

Secondly, these ABM studies can help us to understand the importance of social contexts even when looking at individual behaviour in a more micro-oriented perspective. The role of social influence and the fact that we are embedded in complex social networks have implications for the type of information we access and the types of behaviour we are exposed to. At the same time, individual behaviour has a constructive role in endogenously shaping these networks. While the literature on social networks typically looks at structural factors, the ABM approach can enrich the behavioural counterpart of these studies, providing a more dynamic picture of the interplay of individual behaviour and networks. This could help us to understand the evolutionary bases of network structures, ideally considering a complex set of reciprocal influences between micro and macro levels. It is worth noting that this interplay is difficult to understand using standard social science approaches, given that a combination of qualitative and quantitative factors must be considered simultaneously. Furthermore, simulations can provide a vivid picture of space and time processes that might unfold over a long time, also supporting intuitive understanding of the complexity of social systems.

Here, the advent of the big data movement and the increasing convergence between data platforms in various domains of social life (for example, the public, private and social sectors) could allow sociologists to have fine-grained, large-scale data on individual choices but also on social network connections that were impossible even to contemplate before. By applying sociologically-informed computational models to these multi-source, layer data, we could reveal the complex mechanisms of social life in a globally interconnected world[131].

Finally, one of the most important sociological advantages of ABMs is that they can help sociologists to achieve more rigorous standards of theorization and empirical analysis. ABM studies have developed a serious methodological debate on standards to improve empirical calibration and validation of models, model documentation and reporting and model replication and test[132,133]. Tools such as a public repository of models have been developed (e.g., ABM Open: http://www.openabm.org/), where researchers are asked to make models public so that replication and model extension is easier. This can increase cumulative findings and create the collective dimension of any rigorous scientific endeavour[2].

ABMs can promote a modelling attitude in sociology, including more disciplined theory building and a stronger 'testing hypotheses' experimentalist culture. Moreover, they can make sociology a more collective effort, by undertaking the path followed by more mature disciplines. In this regard, it is worth noting that there is still a serious gap in computing skills in the education programmes of sociologists at all levels, from Bachelors to PhD courses, and even in top institutions. We need to fill this gap in order to equip a new generation of sociologists towards cutting-edge, collaborative research. This is also essential for sociologists to collaborate and compete with external experts, who are increasingly performing relevant sociological research.

Please insert Table 2 here

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Figure captions

Figure 1. Co-existence of behaviours and shirking rate in a typical simulation run (Reference 45, p. 21).

Figure 2. Average number of links per agent in the 'Dynamic2couples' (initial random coupling and broken ties were replaced by only one of the two formerly linked agents) and 'Dynamic2k10couples' (the same but starting from a regular network of degree 10) scenarios (Reference 60, p. 489).

Figure 3. Networks after 30 rounds of a typical simulation run of the 'Dynamic2couples' (left) and the 'Dynamic2k10couples' (right) scenarios (Reference 60, p. 488).

Figure 4. Convergence of the population on a shared convention for each habituation level and for different error probabilities (Reference 65, p. 29). The higher the convergence value, the larger the diffusion of any given right/left convention.

Figure 5. Residential segregation in the NetLogo Schelling's segregation model with household threshold preferences of similar neighbours at 25% (a), 33% (b) and 50% (c)[134].

Tables

Table 1. The impact of referee behaviour on the quality and efficiency of peer review in various selective environments (values expressed as percentage) (Reference 31, p. 4.3). In

‘No reciprocity’, the reliability of scientists when referees was random. In ‘Indirect reciprocity’, referees were reliable if published as authors in the previous round, otherwise they reciprocated rejection by being unreliable when referees. In ‘Fairness’, referees were reliable if they had received pertinent evaluations when authors in the previous round, whether they were published or not. The opposite was true in case of impertinent evaluation. Evaluation bias measured the number of low quality articles that were published when they did not deserve it to be. Resource loss measured the average number of resources on the total at the system level that were wasted when authors, which deserved to be published, were not, compared with the optimal solution, i.e., when only the best authors were published. Reviewing expenses measured the percentage of resources spent by agents for reviewing compared with the resources invested by submitting authors.

Table 2. Summary of the most sociologically relevant ABM studies.

Related Articles

Article ID	Article title
213	Computational social science
231	Network science