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A micro-level simulation for the prediction of intention and behavior

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Abstract

In this contribution we aim at anchoring Agent-Based Modeling (ABM) simulations in actual models of human psychology. More specifically, we apply unidirectional ABM to social psychological models using low level agents (i.e., intra-individual) to examine whether they generate better predictions, in comparison to standard statistical approaches, concerning the intentions of performing a behavior and the behavior. Moreover, this contribution tests to what extent the predictive validity of models of attitude such as the Theory of Planned Behavior (TPB) or Model of Goal-directed Behavior (MGB) depends on the assumption that peoples' decisions and actions are purely rational. Simulations were therefore run by considering different deviations from rationality of the agents with a trembling hand method. Two data sets concerning respectively the consumption of soft drinks and physical activity were used. Three key findings emerged from the simulations. First, compared to standard statistical approach the agent-based simulation generally improves the prediction of behavior from intention. Second, the improvement in prediction is inversely proportional to the complexity of the underlying theoretical model. Finally, the introduction of varying degrees of deviation from rationality in agents' behavior can lead to an improvement in the goodness of fit of the simulations. By demonstrating the potential of ABM as a complementary perspective to evaluating social psychological models, this contribution underlines the necessity of better defining agents in terms of psychological processes before examining higher levels such as the interactions between individuals.

Keyword: ABM, Models of attitude; Prediction of behavior; Rational decision making

1. Introduction

In social psychology, Fife-Schaw, Sheeran, and Norman (2007) recently presented very interesting work in which, using a model of attitudes, the Theory of Planned Behavior (Ajzen, 1991), as the basic structure, they applied statistical simulations to examine the hypothetical impact of interventions on behaviors. This is an example of what a simulation approach can offer to both theoretical understanding and empirical predictions (see also Cheng, Lam, & Hsu, 2006) in social psychology. A further step along this line would be to use dynamic simulations. As argued by Smith and Conrey (2007), one such approach, Agent-Based Modeling *"...is better able than prevailing approaches to capture the types of complex, dynamic, and interactive processes that are so important in the social world*" (p. 87),"*...do[es] not generally require such simplifying [rationality] assumption*" (p. 93), and deserves to be more widely applied in psychology. Indeed, ABM is a tool to study processes that underlie behavior, linking micro-levels referring to intra-personal processes such as decision making or personality

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differences, and macro-levels referring to interpersonal processes such as social influence, group processes such as norm formation, leadership, intergroup processes such as intergroup bias, and social and cultural processes such as cultural transmission of concepts.

1.1. A complementary approach to social psychological research

ABM is a simulation-based technique developed over the past 15–20 years for the study of complex adaptive systems. A complex adaptive system is defined as a system consisting of a large number of interacting, heterogeneous entities called agents, where interactions occur both within the system and with the system's environment over time. ABM takes a bottom-up approach in the sense that it considers a system's constituents as the basic modeling units. The overall system's behavior is not *a priori* known and emerges from the attributes of the agents over time. This leads to complex feedback processes between the two levels of description, often termed as the micro–macro link.

The process of building an agent-based model begins with a conceptual model of the system based on a combination of established theory and theoretical assumptions which identifies the system components (agents) together with a list of their attributes (constructs) and rules of behavior and interaction (relationships), the environmental variables, as well as the measurable outcomes. Once implemented, the ABM simulation is run in the computer "laboratory", generating output data. The simulation data then is analyzed and compared to actual empirical data to show the implications of the model assumptions. This last step, often described as model validation, is arguably the most challenging part of the whole process. Typically the model assumptions and/or parameters are systematically varied until the simulation data "mimics" the empirical data. To be fully self-consistent and as Gilbert (2004) points out, the model needs to be validated both at the macro-level by the (aggregate) statistical analysis and comparison of both sets of data and at the micro-level by comparing the micro-level data in order to understand what and how psychological processes lead to the patterns of behavior seen at the macro-level.

A famous example of an ABM approach is Kalick and Hamilton's (1986) multiagent simulation constructed in order to solve the paradox between the fact that the partners' attractiveness levels tend to correlate and the fact that there was no evidence for the preference for others based on matching attractiveness levels but rather a strong preference for the highest level of attractiveness. They created a simulation in which males and females agents with different level of attractiveness interact in order to create couples. In one version of the simulation agents followed a similarity-matching rule whereas in the other they followed an attractiveness-seeking rule. Only when the agents seek highly attractive partners, the results match the empirically observed level of correlation between levels of partners' attractiveness. The reason is that, as more attractive agents will tend to choose more attractive partners early in the interactions, the dynamics of the choices will be such that less attractive agents will be left with a pool of relatively less attractive partners. Therefore, following a simple rule (seeking for the most attractive partner) at the micro-level of the agents leads over time to the emergence of a phenomenon (correlation between attractiveness levels) at the macro-level.

Bonabeau (2002) identified a number of modeling situations where ABM can be seen to have a clear advantage over conventional approaches. These include situations where interactions between agents are non-linear, discontinuous or discrete, where the population of agents is heterogeneous, where the network of patterns of interactions between agents is neither completely regular nor fully random and where agent behavior is time-dependent. Most models in social psychology fit these criteria quite well. Moreover, unlike real life, by arbitrary changing values of parameters, one can test the consequences of varying any factor without ethical or practical concerns (Smith & Conrey, 2007).

However, despite these advantages and with some well known exceptions of the use of ABM (e.g., Axelrod & Hamilton, 1981; Nowak, Szamrej, & Latané, 1990) or other simulation techniques (see Billari, Fent, & Prskawetz, 2006; Hastie & Stasser, 2000; Smith & Conrey, 2007, for reviews), relatively little research has used ABM simulations in the social psychological field. Moreover, in social psychology ABM has been mainly used for the study of macro-level phenomena such as interactions between people in the context of group discussion (e.g., Blikstein, Abrahamson, & Wilensky, 2008; Deffuant & Huet, 2007; Stasser, 1988) and not for the micro-level, with the exception of connectionist modelling or neural networks (e.g., Eiser, Fazio, Stafford, & Prescott, 2003; Lowe, Bennett, Walker, Milne, & Bozionelos, 2003; Sallach, 2003) that focus on an even lower level of abstraction.

1.2. ABM and actual models of human psychology

Indeed, most social simulation models in the ABM literature are built with little reference to actual models of human psychology or cognitive processes (Sun, 2006a). Even models of market dynamics which mainly focused on the social dimension of the agent's behavior (see Gilbert, Jager, Deffuant, & Adjali, 2007; Gilbert & Troitzsch, 2006, for reviews) do not routinely link social simulations with well-established psychological models of human behavior. An exception can be presented by the Consumat model of consumer behavior (Jager, 2000) where the consumer agents' decision rules were loosely based on the Theory of Reasoned Action. Some modelers have tried to integrate more complexity in the behaviors of the agents (e.g., Sallach, 2003; Wooldridge, 2002). Some models in social cognition propose that psychological processes such as person perception, attitude formation and change are the product of the interaction of multiple "nodes" interconnected in "neural networks" or "connectionist models" (e.g., Kunda & Thagard, 1996; Mosler, Schwarz, Ammann, & Gustcher, 2001; Van Overwalle & Heylighen, 2006; Van Overwalle & Siebler, 2005). These are examples of multi-agent models embedding cognitive elements (e.g., beliefs) as lower level agents that both influence and are influenced by other agents following simple rules (Smith & Conrey, 2007). CLARION (Sun, 2006b, 2009; Sun, Merrill, & Peterson, 2001) is certainly one of the most complete framework designed to capture a range of cognitive processes. It is an integrative model that consists in different sub-systems (each with two levels of representation, implicit versus explicit). The four sub-systems include the action-centered sub-system that controls actions (external physical movements or internal mental operations), the non-action-centered sub-system that maintains knowledge (implicit or explicit), the motivational sub-system that provides motivations (implicit – drives or explicit – goals) for perception, action, and cognition, and the meta-cognitive sub-system that regulates the operations of the other sub-systems. One important characteristic of CLARION central to our concerns is the constant interaction of the components, sub-systems and environment, the presence of implicit and explicit cognitions, motivation, meta-cognition to capture realistic psychological processes (Sun & Naveh, 2004).

Besides CLARION, little attention has been devoted to elaborate models simulating individual agents who embody social psychological model variables (e.g., attitudes, subjective norms) interacting with each other within each individual. This approach would have the advantage to better illustrate the heterogeneity of studied populations, and to be able to relax many of the restricting assumptions like rationality that are implicit in standard statistical approaches. There is therefore room for building multi-agent models embedding the constructs of well-known social psychological theoretical models. This is an essential first step that provides the foundation at the micro-level before further developments that may examine interactions in social networks (macro-level). In this perspective, the approach used here focuses on the micro-level of the ABM which considers only intra-individual processes and not the interaction between individuals. The ABM approach considering micro-agents as mental constructs and macro-agents as individuals who do not interact may appear at first sight divergent from a "typical" ABM focus on examining interactions between agents usually defined as individuals. However, Smith and Conrey (2007) themselves pointed out that although typically agents represents individual persons, they "*...can be used to represent entities at other levels, whether lower level (neural networks) or higher (social groups, organizations, economic actors)*" (p. 101). In this contribution we focus on lower level agents categories – intra-individual – of ABM. Hence, this work contributes towards reversing the usual tendency that, "*most of the work in social simulation still assumes very rudimentary cognition on the part of agents*" (Sun, 2006a, p. 6, see also Sun, 2004).

1.3. Models of attitude: Theory of Planned Behavior (TPB) and Model of Goal-directed Behavior (MGB)

The Theory of Reasoned Action (TRA, Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and its extension, the Theory of Planned Behavior (TPB, Ajzen, 1991, 2004; Ajzen & Madden, 1986) are among the most known and widely adopted models of attitudes. The TRA suggests that people act in accordance with their Intentions that are in turn influenced by Attitudes toward the behavior (i.e., degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question) and Subjective Norms (i.e., perceived social pressure to perform or not to perform the behavior). According to its follower, the TPB, people act in accordance with their Intentions and Perceived Behavioral Control (i.e., perceived ease or difficulty of performing the behavior). Intentions, in turn, are influenced by Attitudes, Subjective Norms, and Perceived Behavioral Control. Despite numerous validations of its predictive power (for a meta-analysis, see Armitage & Conner, 2001), the TPB is not exhaustive and there is room for improving the part of variance explained in Intention and Behavior (e.g., Sheeran & Orbell, 1999).

In the light of this analysis, Perugini and colleagues (Perugini & Bagozzi, 2001, 2004a, 2004b; Perugini & Conner, 2000) proposed the MGB in order to expand and deepen the TPB by incorporating constructs from three new theoretical areas (affective, motivational and automatic processes). In the MGB, Intention to perform behavior is primarily affected by the Desire to perform the behavior (i.e., personal motivation or wish to perform the action) and this Behavioral Desire is assumed to reflect the effects of Attitude, Subjective Norms, Perceived Behavioral Control and Anticipated Emotions (i.e., anticipated affective reactions to failure and success to perform the action) and to mediate their influence on Intention. The MGB also includes frequency and recency of past behavior to incorporate the influence of automatic and habitual aspects in decision making not reflected by the variables of the TPB.[1] The predictive power of the MGB has been demonstrated for different behaviors such as weight control, studying and traveling (e.g., Dijst, Farag, & Schwanen, 2007; Leone, Perugini, & Ercolani, 2004; Perugini & Bagozzi, 2001; Perugini & Conner, 2000; Richetin, Perugini, Adjali, & Hurling, 2008; Taylor, 2007; Taylor, Bagozzi, & Gaither, 2001). The MGB explained from 26% to 46% more variance in intentions than the TPB (Perugini & Bagozzi, 2004b) but the improvement is not very strong for behavior due to the main focus of the MGB on modeling pre rather than post-volitional processes. In some senses, the

[1] In this contribution, the role of past behaviour will not be examined in the prediction of behaviour because of its controversial theoretical status (cf. Ajzen, 2004).

CLARION model follows a similar logic in the action decision making process. For example, in the action-centered system, the overall algorithm consists, after having observed the current state of the system (1), in choosing an action based on its value compared to other possible actions at the bottom level (implicit, 2) as well as at the top level (explicit, 3), then choosing an appropriate action by stochastically choosing the outcome of either the top level or the bottom level (4), performing the action (5), and updating all levels based on the feedback (6). CLARION describes the action decision making process by a series of steps that can be compared to the process in the MGB in which the individual will consider different parameters (e.g., attitude, subjective norms, desires) before initiating a behavior.

1.4. Rationality in decision making

The TRA (Fishbein & Ajzen, 1975) and all derived models assume logical consistency or rationality between individuals' belief sets, Attitude, Intention and Behavior. However, the concept of Intention–Behavior gap for example illustrates the limitations of the models in predicting behavior based on intentions (Sheeran, 2002). Indeed, people do not always act upon their intentions (e.g., inclined abstainers, see Orbell & Sheeran, 1998). When considering the MGB, even if the inclusion of additional variables improves the prediction of Intention, there is still room for improvement. This is also true for the link between Behavioral Desire and Intention given that the average variance explained in Behavioral Desire is around 70% (Perugini & Bagozzi, 2004b). More importantly, although the MGB is more complex than the TPB given its attempt to specify processes that are not covered very well by this latter model, both models rely implicitly on the assumption of rationality. For example, for both models, given a set of appraisals on different aspects of a decision problem (e.g., attitude, subjective norms, anticipated emotions), people should follow them up – that is, if one would particularly like to jog next week he/she should intend to do so and then act upon his/her intention.

However, as noted by Shafir and LeBoeuf (2002), although considering the individuals as purely rational has been the predominant view in the social sciences for modeling and predicting human behavior, with the introduction of the notions of bounded rationality (Simon, 1955), of heuristics or framing effects (e.g., Kahneman & Tversky, 1973, 2000; Tversky & Kahneman, 1981, 1983), the rationality assumption has started to be considered as inadequate for predicting behavior. In this perspective, Sapp (2001) showed that the observed inconsistency or non-rationality in beliefs created bias in the interpretations of the effects of beliefs on attitudes and on subsequent intention and behavior. Moreover, he showed that models accounting for non-rationality in beliefs provided a better fit to the data than models using standard measures of beliefs and attitudes. Similarly, Grieve (2001) has criticized the so called Logical Connection Argument (LCA), using the TPB as one prominent example of such assumption, because intention does not imply action nor action implies a preceding intention unless one assumes a fully rational actor.

Taken together, these theoretical and empirical findings suggest that one cannot assume that decision making is strictly driven by rationality and should leave some space for inconsistency or non-rationality in the link between variables such as intention–behavior. However, it is likely that, everything else being equal, this "irrationality" gap is smaller for more complex and comprehensive models such as the MGB relative to the TPB because more comprehensive models include additional variables in the prediction of the construct of interest and thus should reduce the gap.

1.5. Aim of this contribution and hypotheses

This contribution aims at illustrating the usefulness of an ABM approach by applying it at the micro-level to two social psychological models of attitude and comparing it with standard statistical approaches. This constitutes an essential first step in defining and validating agents as individuals before further work that may examine their interactions within social networks. We focused on the TPB and MGB models, and used real data and ABM simulations in which micro-agents embodied the TPB and MGB variables and macro-agents represent the individual as a whole whose behavior is an outcome of the interaction between the micro-agents according to the behavioral model under consideration. Although one advantage of ABM simulation is that it allows considering reciprocal relationships between elements, we chose to define the relationships between the micro-agents as unidirectional in order to strictly reproduce the two models of attitude. Real data about drinking fizzy soft drinks were collected through a questionnaire study, and each model was tested with Structural Equation Models (see Richetin et al., 2008). The collected data were then used to build two ABMs to simulate the TPB and MGB. This first step is the transposition of theoretical models of relations into a computer program. The distributions of intention, behavioral desire (MGB only) and behavior from the two simulated models were compared to the distributions from the step-wise regressions. This constitutes an essential step in simulations: The simulation model is considered valid if the original findings can be replicated. Then only when the simulation model has been validated, simulation experiments can be run. We focused here on rationality in the decision making process. The possibility of a deviation from the model in macro agents' decision process (lack of rationality) was introduced in the simulation to see whether it influences the predictive power of the models. Finally, a second set of real data about undertaking vigorous physical activity was used in order to examine whether the key results of the first simulation were replicated. Three main hypotheses were tested. First, we hypothesized that the simulation would replicate the empirical findings and even improve the goodness of fit for Behavioral Desire (only MGB), for Intention and Behavior (H1). We also expected that by introducing in the simulation a reasonably small deviation from rationality in the decision making process it would improve the goodness of fit whereas a great deviation would make it worse (H2). Finally, we hypothesized that the improvement of the predictions from simulation would be inversely proportional to the complexity of the theoretical model (H3).

2. Data Set 1 on drinking fizzy soft drinks

2.1. Step I: Data collection and baseline results

As mentioned above, the real data about drinking fizzy soft drinks were collected through a questionnaire study.

2.1.1. Participants and procedure

Seventy-five women and thirty three men (M age = 23.8, $SD = 5.97$) participated in a three session study with one week intervals. In the first session, each participant sat individually in a cubicle at a table with a desktop computer and completed a questionnaire with measures toward drinking fizzy soft drinks. The questionnaire contained:

(a) A measure of Attitude (ATT, $\alpha = .89$) that consists in presenting the stem "For me, drinking fizzy soft drinks is" followed by six bipolar items (i.e., bad/good, unpleasant/pleasant, negative/positive, unenjoyable/enjoyable, unhealthy/healthy, unsatisfying/satisfying) on 7-step answer scales ranging from 1 (very bad) to 7 (very good).
(b) Two items measuring Subjective Norms (SN, $r = .45$) "People who are important to me would approve of my drinking fizzy soft drinks" and "People who are important to me would be very happy if I drink fizzy soft drinks" on 7-point scales from 1 to 7.
(c) Two items (measuring Perceived Behavioral Control (PBC, $r = .55$), "How much control do you have over drinking fizzy soft drinks?" and "If I wanted to, it would be easy for me to drink fizzy soft drinks" on 7-point scales from 1 to 7.
(d) Ten items assessing Positive and Negative Anticipated Emotions (PAE, NAE, $\alpha = .87$ and .90, respectively) on a 7-point scale ranging from 1 (not at all) to 7 (extremely). Participants indicated how (delighted, disappointed, embarrassed, gratified, guilty, happy, pleased, regretful, satisfied, worried) they would feel should they drink fizzy soft drinks. Half of the adjectives referred to negative and half to positive anticipated emotions.
(e) Three items measuring Behavioral Desire (BD, $\alpha = .94$), "How strongly would you characterize your desire to drink fizzy soft drinks?" which was rated on a 6-point scale from 1 (no desire) to 6 (very strong desire), "I desire to drink fizzy soft drinks," which was rated on a 7-point scale ranging from 1 (unlikely) to 7 (likely); and (3) "Drinking fizzy soft drinks is something that I desire to do," which was rated on a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree).
(f) Three items measuring Intention (INT, $\alpha = .95$), "I will drink fizzy soft drinks," "How likely is that you will drink fizzy soft drinks?", "I intend to drink fizzy soft drinks" with 7-point scales ranging from 1 to 7.

The study included some additional measures that will not be considered because they are not relevant for this contribution. In the second and third sessions, participants completed a self-reported grid concerning their last week consumption of a series of fizzy soft drinks (e.g., Coke, Pepsi, Sprite, lemonade) ($r = .84$) expressed in units (e.g., a can of 330 ml equals one unit). Participants were asked to report how many in each category they drank during the last week. Finally, the participants were debriefed, thanked for their participation and paid. The data from three participants were discarded because they did not attend the last session, leaving a total of 105. Additional details are reported in Richetin et al. (2008).

2.1.2. Baseline results

The regression (see below for details) results showed that for the TPB and MGB predictors accounted for 59.4% of the variance in the Behavioral Desire to drink fizzy soft drinks (only MGB), for 49.7% and 55.4% of the variance in Intention to drink fizzy soft drinks and for 19.3% and 20.5% of the variance in Behavior.

2.2. Step II: ABM simulation

2.2.1. Method

The analysis carried out involves agent-based simulations on the empirical data, with the TPB and MGB as the base. As specified before, at the macro-level of individuals, agents do not interact. The attention is focused on the unidirectional links between micro-agents that are the TPB and MGB constructs for the emergence of behavior. All simulations were developed within the .NET framework using C# as the programming language. These simulations are not a strict substitute to rigorous statistical analysis but are an extension to it, in order to obtain better results. Any form of statistical analysis, even sophisticated, ignores the heterogeneity in the population of individuals, while with ABM simulations the heterogeneity is reintroduced back into the analysis. This approach additionally allows one to experiment with parameters such as individual's rationality, something which is difficult to address with a purely statistical approach.

The ABM approach used was neither purely simulation based, nor purely statistical, but a hybrid of the two. This approach allows direct comparison of ABM with standard statistical methodologies, whilst retaining the potential advantages of ABM. Technically, robust estimation techniques were used in order to extract the best possible statistical fits to the underlying theoretical model (Erceg-Hurn &

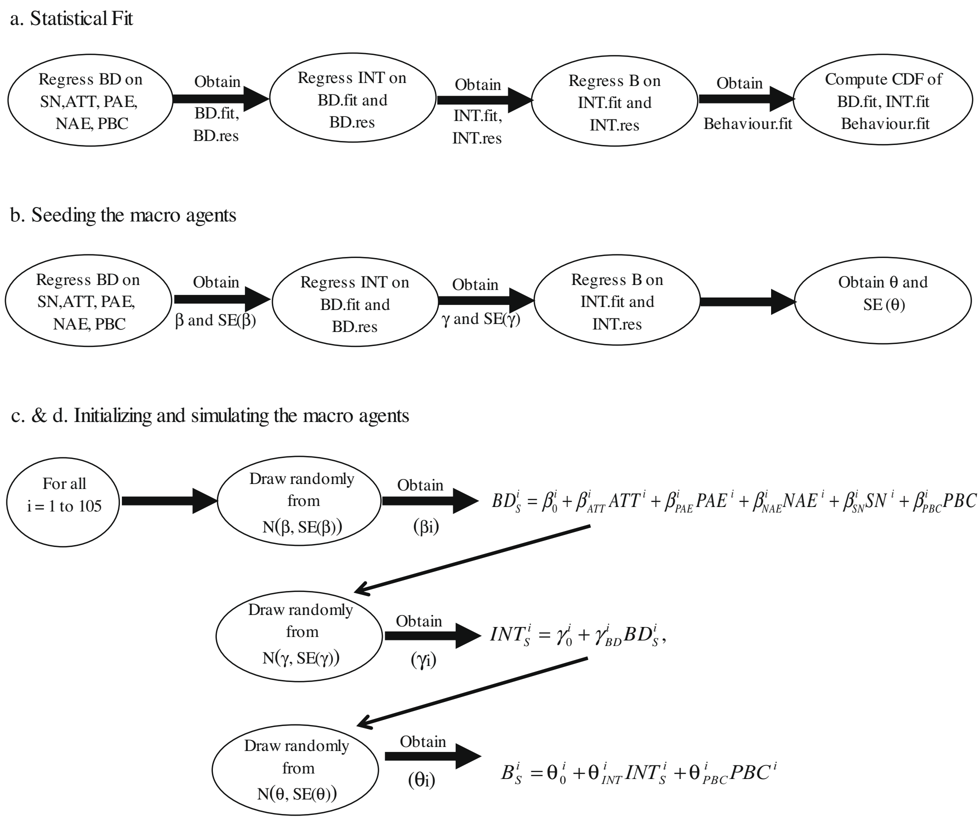

Fig. 1. Flow diagrams of all stages in the estimation and simulation processes for MGB.

Mirosevich, 2008; Wilcox, 2005) and then the "unconditional" estimated parameters were used as a base in the simulations in order to introduce the heterogeneity. The aim was to see if this approach leads to better fit to the empirical data as opposed to the purely statistical one. Once the results had been analyzed, opportunities of introducing the additional aspects of rationality or the lack thereof were examined. All regressions have been carried out using the Robust Method of Moments Estimation method, which handles outliers in the data better than most other methods (for details, see Yohai, Stahel, & Zamar, 1991).[2] The stages in the analysis are detailed below (cf. Fig. 1 for the set of flow diagrams).

1. *Determining the standard statistical fit* consisted of considering the two models (TPB and MGB) and estimating step-wise linear regression coefficients of each for defining the micro-agents. Taking the MGB model as an example, the first step involved BD being regressed on ATT, PAE, NAE, SN and PBC in order to get the estimated BD (BD.fit) and the residuals (BD.res). As a second step, INT was regressed on BD.fit and BD.res with the former taking into account the effects of the first step variables and with the latter adjusting for the unexplained variation in BD. This gave the fitted Intention (INT.fit) and the residual (INT.res) which, in turn were used to estimate the linear regression on Behavior.[3] Empirical Cumulative Distribution Functions (CDFs) were constructed from the fitted/estimated variables. Note that the parameter estimates are "conditional" estimates, where independent variables at each step are the fitted values from the previous step – hence estimates in the current step are conditioned on those from the previous.
2. *Seeding the macro-agents*: A similar set of step-wise regressions as in stage 1 was carried out, but now with the intermediate regressions (e.g., BD on INT) based on the *measured* values of the variables themselves as opposed to the fits and residuals. These "unconditional" parameter estimates and the corresponding standard errors for every regression were recorded[4] to be used in stage 3.

[2] The reasons for using Robust regression were threefold. Firstly, nothing in the data suggested that the regression disturbances were normally distributed. Secondly, the presence of a few outliers and the size of the sample required the use of robust techniques capable of handling them. Finally, note that Robust methods are considered as technically superior to standard methods (e.g., OLS) as convincingly argued for instance by Erceg-Hurn and Mirosevich (2008).

[3] The parameter estimates at each stage of the model were conditioned on the estimates from the previous stage, via the fitted and the residual values.

[4] Here the parameter estimates were unconditioned on the previous stage within the model and only the measured values from the data were being used in the estimation. The estimated means and variances were used only as a medium to randomly draw the agents, in the introduction of heterogeneity alone. They did not play any other role in the simulation.

3. *Initializing the macro-agents*: Based on the number of the participants, 105 normally distributed random parameter sets were drawn, with each set representing one macro-agent in the following manner. Each estimated link (coefficient vector) in stage 2 were considered as the mean and the corresponding standard errors as the standard deviations for the 105 random draws. The resulting macro-agent specific data consists of the measured micro-agents plus the random parameter set specific to the agent, representing the interaction between the micro-agents. As an example, consider MGB and the relationship between micro-agent BD and ATT, PAE, NAE, SN, PBC. The estimated vector of regression coefficients is given by, $(\beta_0, \beta_{ATT}, \beta_{PAE}, \beta_{NAE}, \beta_{SN}, \beta_{PBC})$, with a corresponding vector of standard errors. Hence, 105 independent $(\beta_0^i, \beta_{ATT}^i, \beta_{PAE}^i, \beta_{NAE}^i, \beta_{SN}^i, \beta_{PBC}^i)$ vectors are drawn from normal distributions with corresponding means and standard deviations. Each vector superscripted by *i* represents a macro-agent specific link between the relevant micro-agents.
4. *Simulating the macro-agents*: Each macro-agent was run through the specified model conditional on the stage 1 variables only. Taking the MGB model as an illustration, each macro-agent was initialized with the measured values of ATT, PAE, NAE, SN and PBC and its draw of the random coefficients which link these variables to BD. Consider macro-agent *i* with the vector of random coefficients assigned to it as,

   $(\beta_0^i, \beta_{ATT}^i, \beta_{PAE}^i, \beta_{NAE}^i, \beta_{SN}^i, \beta_{PBC}^i)$

   this agent's BD is then calculated as,

   $$BD_S^i = \beta_0^i + \beta_{ATT}^i ATT^i + \beta_{PAE}^i PAE^i + \beta_{NAE}^i NAE^i + \beta_{SN}^i SN^i + \beta_{PBC}^i PBC^i \quad (1)$$

   where BD_S^i was the simulated BD for agent *i* given the random draw of coefficients and the underlying measured data. Once this stage of simulating BD was completed for all 105 macro-agents, INT was simulated for every macro-agent, conditional on the previous simulation. Considering the vector of coefficients as,

   $\gamma_0^i, \gamma_{BD}^i$

   Then *i*'s INT is calculated as,

   $$INT_S^i = \gamma_0^i + \gamma_{bd}^I BD_S^i \quad (2)$$

   where the second step simulation of INT is conditional on the first step simulation of BD. And finally, the last step simulation of Behavior is carried out similarly using the vector of coefficients $(\theta_0^i, \theta_{INT}^i, \theta_{PBC}^i)$, in the following manner,

   $$B_S^i = \theta_0^i + \theta_{INT}^i INT_S^i + \theta_{PBC}^i PBC^i \quad (3)$$

5. *Recording the outcome*. The simulated values were stored in an external file. Stages 4 and 5 were repeated for both TPB and MGB.
6. *Introducing deviation from rationality*. At this stage, different degrees of rationality were introduced into the analysis. We allow the macro-agent to deviate from the regular path at the micro-level by way of a *trembling hand* refinement first introduced by Selten (1975, 1983) in game theory, which is a convenient way of introducing degrees of irrationality within the agents.[5] This concept can be easily adapted for ABM-type simulations where individual agents may not behave rationally all the time. We choose to operationalize deviation from rationality as a random choice. Following the standard definition, a rational choice is one which is consistent with beliefs behind the choice itself (cf. Grieve, 2001). This also implies, for instance, that being biased or making suboptimal decisions does not necessarily mean being irrational (cf. McKenzie, 2003). A random choice is by definition irrational when it is done despite existing beliefs. Its irrationality is a consequence of being random which by definition implies that it does not follow one's underlying beliefs or evaluations. We introduce this by assuming that individuals can randomly deviate from their Behavioral Desire or Intention a certain number of times. The overall procedure remains the same as above till stage 3, at which point a new parameter (probability *p*) was introduced into the analysis. The parameter *p* represented the probability with which individual agents choose to obey the models specified in Eqs. (1), (2) and (3). Conversely, with probability $(1 - p)$, the macro-agent was assumed to act irrationally and chose any level of BD, INT or Behavior completely at random.[6] The value of *p* was chosen at the beginning of the simulation process. As choice now becomes a stochastic process, the results are presented as averages of multiple runs with the same set of macro-agents.

The steps described above lead to a set of simulated values for BD, INT and Behavior for our sample of 105 macro-agents. Individually, each macro-agent's simulated output was not expected to correlate strongly with the corresponding real value. This is because, although participant *i*'s initial data was used for the seeding of macro-agent *i*, the actual *model* for agent *i* combined the random draws from stage 3 as well. Hence each macro-agent has his own model of behavior which is likely to be different from any other agent (unless the initial seeding micro-agent values and the random draws were exactly the same for two agents). This is in fact, how we introduced heterogeneity into the system by way of ABM, which standard statistical

[5] The trembling hand is a classic concept in the field of economics in general and in game theory in particular for which Selten was awarded the Nobel Prize in 1994. The basic idea is that one player, through a "slip of the hand" or tremble, can employ with a certain small probability an unintended action (error).

[6] Making an irrational decision at a particular stage in the decision process (i.e., BD, INT or SRB stage) does not affect the probability of making an irrational decision in a subsequent stage.

analysis is unable to capture. The aim was to see whether the *distribution* of the simulated output matched the real distribution better than the estimated one. Moreover, given that in the rational case, there is no randomness in the simulations (Step 4), we do not need to run the simulations multiple times. Every run is exactly the same once the random draws are made and macro-agents are initialized in Step 3.

2.2.2. Results

The initial set of results from the ABM was compared against the standard statistical results as well as the real data. Comparisons are done both graphically and via a statistical measure on the simulated, estimated and real data on both models. All simulations were run 10000 times and the average results presented. In the case of rational choice it does not matter how many times the simulations were run, but for the irrationality case 10000 runs was considered a large enough number to smooth out the noise component within a reasonable amount of time.

The results were evaluated in terms of simulated, estimated and real cumulative frequency distributions (CDFs, for an example for Intention see Fig. 2) rather than the goodness of fit or any other measure which makes a one-to-one comparison of every macro-agent or participant in the sample. Given the randomness on the links between the micro-agents, each macro-agent only partially represented the real person in the sample, and hence a direct one-to-one comparison is not appropriate for evaluation of results. Our evaluation of the goodness-of-fit is done at the level of the distributions (CDFs).

The statistic used for the comparison of distributions of two variables was the root mean squared difference (RMSD) of ordered data.[7] That is, for any two ordered variables X and Y, we define.

$$\mathrm{RMSD}_{X,Y} = \frac{1}{N}\sqrt{\sum_{i-1}^{N}(x_i - y_i)^2}$$

where N is the total number of observations.

Table 1 reports the RMSD calculations for both estimated and simulated values, when the deviations have been benchmarked against real values. This has been carried out for all variables for all models, and then repeated for varying degrees of irrationality. The percentages of improvement in fitness in the simulated distribution relative to the estimated distribution and Pearson's correlation coefficients between the estimated or simulated distribution and the real distribution are also reported. Note that a decrease in RMSD is seen as an improvement in the fit and vice versa. Also note that, in terms of estimated distributions, MGB performs better than the TPB when RMSDs are compared (for Intention and Behavior, respectively, .036 and .362 for MGB while .058 and .371 for TPB).

2.2.2.1. Simulations versus estimates within models. The results primarily examined whether simulations improved the fit of the distributions within a given social psychological model. Simulations were almost invariably better than estimates in predicting the actual distribution (see Table 1, TPB Rational and MGB Rational cases), especially in case of Behavior. In Behavior, where the estimates of both models were especially poor in predictions, simulations lead to a significant improvement: 22% for TPB and 16% for MGB. This improvement is corroborated by the coefficient correlations that indicate that the statistical estimates performed poorer for both TPB and MGB (.772 and.785) than the simulation (.872 and.885). Therefore, H1 was supported.

2.2.2.2. Simulations versus estimates with deviations from rationality. The changes in results due to the introduction of a deviation from rationality in the simulations were then examined in relation to comparisons made within models. Using the trembling hand approach, the possibility of a random choice was allowed in an agent's decision process, where the degree of deviation from rationality is fixed at a certain level representing the proportion of times an agent is allowed to deviate from the underlying model. Four different degrees of deviations were separately introduced, 5% (which indicates that an agent deviate from the model 5 times out of 100), 10%, 20% and 50%.

With the degree of deviation fixed at 5%, the results show that the simulated distribution always fitted the experimental data better than did the statistical fit. There was an improvement in goodness of fit at the level of Behavioral Desire (for MGB), Intention (for TPB and MGB) and Behavior (for both TPB and MGB). With the degree of deviation fixed at 10%, the improvement in goodness of fit was noted only for Behavior for both the TPB and the MGB. With 20%, there was still an improvement for Behavior (TPB and MGB) and for Intention for the TPB. Finally, with 50% of deviation from rationality, there was no improvement with the exception of Behavior for TPB. Therefore, the introduction of a reasonable degree of deviation from rationality improves fitness at the level of the distribution, particularly for the TPB, whereas a much greater degree makes the fit worse, supporting H2. Note that, a 5% deviation from rationality is "optimum" for both models, in the sense that it induces the greatest improvement in fit in distribution.

2.2.2.3. Simulations versus estimates with increasing complexity. Finally, the performances of simulations were examined as the complexity of the underlying social psychological model increases (i.e., from TPB to MGB). Only the prediction of Intention was considered given that Behavioral Desire is a construct only in the MGB and given that Behavior is predicted by the same variables

[7] Each variable was separately ordered in ascending order. The CDFs themselves were constructed using ordered data. Also, given that a simulated macro-agent only partially represented a real individual, and that only distributions were compared, changing the ordering did not hamper the results. However, one needs to make sure that the ordering is consistent in *all* the variables.

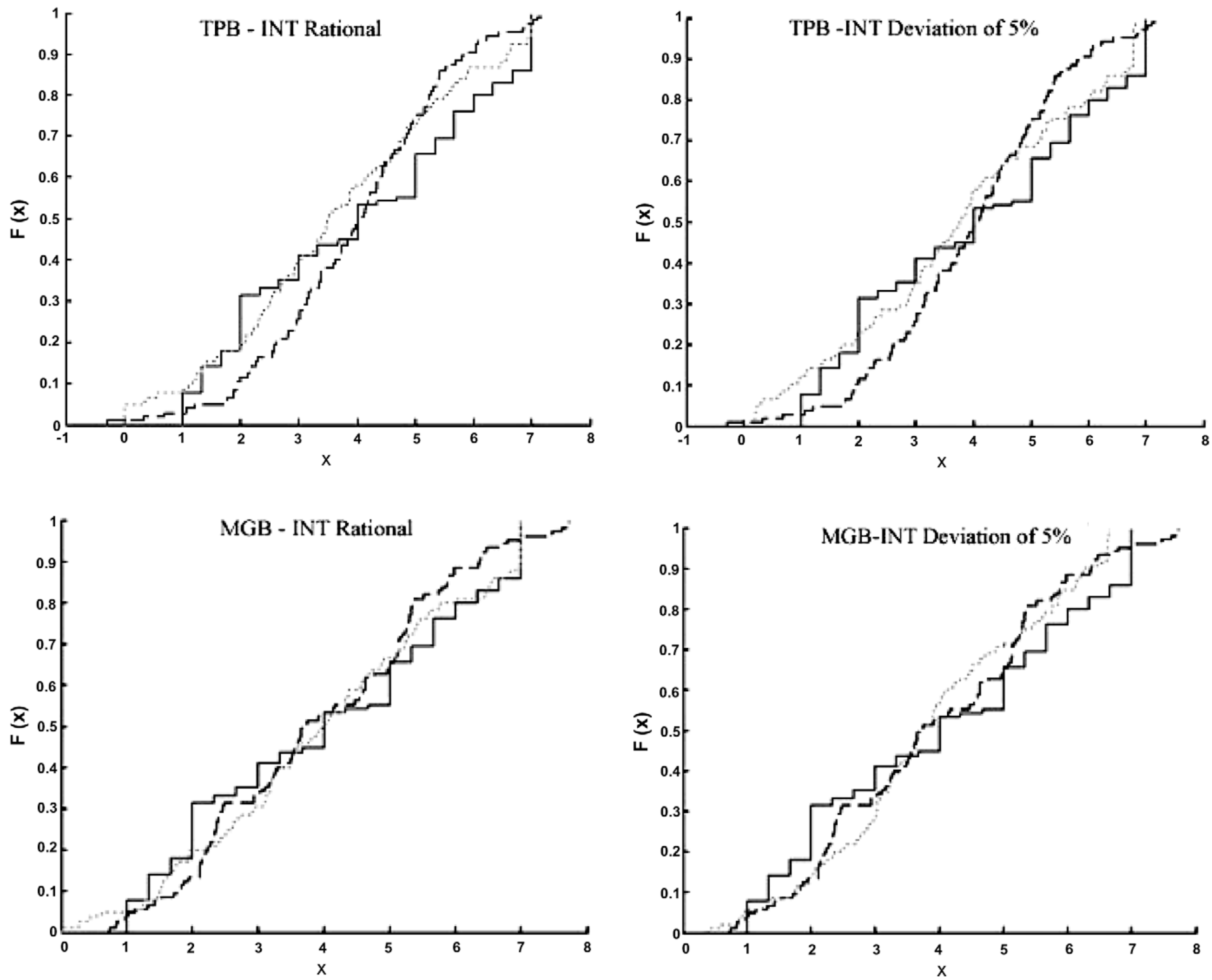

Fig. 2. Simulated, estimated and the measured cumulative frequency distributions (CDFs) for the TPB and MGB for predicting intention, rational and deviation of 5%. Note for Fig. 2: (—), measured CDF; (- -), estimated CDF; (⋯⋯), simulated CDF. x = Values of the variable. $F(x)$ = Cumulative frequency distribution (CDF).

Table 1
Comparison summary results for the Simulation from Data Set 1 on drinking fizzy soft drinks.

	Behavioral Desire				Intention				Behavior			
	Estimated		Simulated		Estimated		Simulated		Estimated		Simulated	
	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*
TPB rational	na	na	na	na	.058	.956	.033 (43%)	*.979*	.371	.772	.288 (22%)	*.872*
TPB deviation of 5%	na	na	na	na	.058	.956	.044 (24%)	*.967*	.371	.772	.278 (25%)	*.914*
TPB deviation of 10%	na	na	na	na	.058	.956	.060 (−3%)	*.963*	.371	.772	.309 (17%)	*.866*
TPB deviation of 20%	na	na	na	na	.058	.956	.047 (20%)	*.985*	.371	.772	.318 (14%)	*.844*
TPB deviation of 50%	na	na	na	na	.058	.956	.090 (−55%)	*.982*	.371	.772	.354 (4%)	*.906*
MGB rational	.035	.968	.024 (14%)	*.981*	.036	.981	.048 (−33%)	.966	.362	.785	.304 (16%)	*.885*
MGB deviation of 5%	.035	.968	.023 (34%)	*.986*	.036	.981	.031 (14%)	*.987*	.362	.785	.287 (21%)	*.879*
MGB deviation of 10%	.035	.968	.029 (17%)	*.975*	.036	.981	.057 (−73%)	.965	.362	.785	.311 (14%)	*.881*
MGB deviation of 20%	.035	.968	.038 (−8%)	*.973*	.036	.981	.077 (−58%)	.970	.362	.785	.321 (11%)	*.844*
MGB deviation of 50%	.035	.968	.069 (−97%)	*.976*	.036	.981	.127 (−252%)	.959	.362	.785	.371 (−2%)	*.820*

Note: Percentages of improvement or decrease in fitness in the simulated distribution relative to the estimated distribution are indicated into brackets. The underlined percentages indicate an improvement of the simulation over the estimate. The correlations in italics indicate an improvement of the simulation over the estimate.

(Intention and PBC) in both models. Explanation of variation in Intention decreased with the complexity (RMSD of 0.058 and 0.036, respectively) which is coherent with the percentages of variance explained to start with ($R^2 = .20$ and .19, respectively). Focusing only on rationality results, there was no improvement in the fit for Intention for the MGB (−33%) whereas there was for the TPB (43%). Similarly, when considering the degrees of deviation from rationality results, the improvement in the fit was lower for the MGB than for the TPB. Hence, for those variables where statistical estimation gave reasonably good results, the improvement to predictions using simulations was inversely related to the complexity of the underlying model, supporting H3.

To sum up, the results based on the first data set show that simulation improves the prediction of Behavioral Desire (for MGB), and of Intention and Behavior for both models. Moreover, the introduction of a small degree of deviation from rationality improves the prediction in most of the cases. Finally, the improvement in predictions using simulations is greater for simpler models like the TPB than for more complex models like the MGB, the latter exhibiting a better statistical fit than the former. Taken together, these results illustrate the importance of an agent based approach, for instance in explaining the transition from Intention to Behavior – where current models and approaches perform poorly, simulations improve them significantly. A replication of this method on a new set of data would allow for a generalization of these results.

3. Data Set 2 on doing vigorous physical activity

3.1. Step I

3.1.1. Method

3.1.1.1. Participants and procedure. A hundred and forty three participants (53 men, 90 women, M Age = 22.27, $SD = 3.95$) from an Italian University participated in a two sessions study with a one week interval. In the first session, each participant sat individually in a cubicle at a table with a desktop computer completed a set of measures. The stems of the measures were as for Study 1, except that this time they referred to perform vigorous physical activity (defined as vigorous physical activity of at least 20 min for at least 3 days a week). Specifically, seven items for Attitude (ATT, $\alpha = .87$), three items for Subjective Norms (SN, $\alpha = .85$), three items for Perceived Behavioral Control (PBC, $\alpha = .77$), five items each for Positive and Negative Anticipated Emotions (PAE and NAE, $\alpha = .88$ and $\alpha = .92$, respectively), three items for Behavioral Desire (BD, $\alpha = .96$), and Intention (INT, $\alpha = .96$) to do vigorous physical activity. The measures were administered via computer (Inquisit software Web edition) in the order mentioned above. In the second session, all participants completed self-reported behavioral measures concerning doing vigorous physical activity. These were the items concerning vigorous physical activity of the official Italian translation of the IPAQ (Booth, 2000) and the Godin's questionnaire (Godin & Shephard, 1985), which are considered among the best available self-reported behavioral measures and have been validated against objective criteria. Given the highly significant correlation ($r = .66$), the items were averaged in a single behavioral measure of vigorous physical activity. Finally, participants were thanked for their participation and debriefed. Eleven participants did not attend to the second session, leaving a total of 132.

3.1.1.2. Baseline results. The regression for the two models showed that that for the TPB and MGB predictors accounted for 65.4% of the variance in the Behavioral Desire to drink fizzy soft drinks (only MGB), for 42.3% and 46.3% of the variance in Intention to drink fizzy soft drinks and for 34.2% and 33% of the variance in Behavior.

3.2. Step II

3.2.1. Method

The method for the simulations was identical to that described in the first study. Specifically, all simulations of the two models were developed within the .NET framework using C# as the programming language according to the five stages (i.e., determining the standard statistical fit, seeding the agent distributions, initializing the agents, simulating the agents and recording the outcome), except that this time 132 agents were initialized. Finally, like with Data Set 1, the simulations were also run with the trembling hand modification (i.e., degrees of deviation from rationality) of 5%, 10%, 20% and 50%.

3.2.2. Results

As before, the initial set of results from the ABM was compared against the standard statistical results as well as the real data. In terms of the RMSD for the estimated distribution of the TPB versus the MGB, the MGB performed significantly better in Intention (.051 versus .042) whereas they were equivalent for Behaviour (.070 versus.069).

3.2.2.1. Simulations versus estimates within models. In the case of fully rational agents, the simulations were significantly better than estimates in predicting the empirical distribution for the TPB whereas for the MGB, the simulations were worse for all three variables (i.e., BD, Intention and Behavior), which does not support H1. This discrepancy with data set 1 can be explained on the basis that, compared to the results from data set on drinking fizzy soft drinks, the estimates of both models were much better in predictions, especially for Behavior (RMSD = .371 and .069), as confirmed by the variance explained in the baseline regressions (.34 and .33, respectively). As a consequence, there is less room for improvement with the simulations.

3.2.2.2. Simulations versus estimates with deviations from rationality. For the TPB, in line with the results from the first data set, with the introduction of 5% and 10% of deviation the simulated distribution better fitted the real data as compared to the estimated. For the MGB, no improvement in the fit was present for both Behavior and Intention considering all different degrees. All degrees of deviation above 10% led to worse fit for all the variables in both models with the exception of a deviation of 20% for Intention for the TPB. Therefore, given the nature of the data, it appears that the introduction of a reasonably small degree of deviation improved the fitness of the simulated distribution but only for the TPB, and that any greater deviation worsens the results. Therefore, H2 is only partially supported. Once again, 5% deviation from rationality seems be the optimal, even in the case of MGB.

3.2.2.3. Simulations versus estimates with increasing complexity. From the results of the two previous sections, it appears that considering either the rationality or the degrees of deviation from rationality, the improvement in the fit was present for the TPB but not for the MGB. Therefore, the results are in line with the results from the first data set and support the idea that the improvement is greater for simpler models, supporting H3.

4. General discussion

Using ABM at the micro-level as a novel approach for simulating social psychological models and using real data from two domains (i.e., drinking fizzy soft drinks and doing vigorous physical activity), this contribution aimed at simulating two models of attitudes (i.e., TPB and MGB) to see how they perform and whether they would lead to improved predictions under particular conditions. The use of ABM showed that simulations of TPB (from both data sets) and MGB (only from data set 1) are better than standard statistical estimates in predicting the real distributions. It is important to highlight that we have used one of the best available statistical methods (robust method of moments) that are currently advocated as the new frontier in statistical data analysis (cf. Erceg-Hurn & Mirosevich, 2008). It is therefore worth emphasizing that an ABM approach is able to provide improved results even in comparison to the best statistical methods available. Moreover, the inclusion of a reasonable deviation from the model through the introduction of degrees of deviation from rationality of 5% and 10% improves the goodness of fit for TPB, for Intention and Behavior in both data sets, for MGB in the first data set and the inclusion of any greater deviation from rationality tends to worsen the fit for both models at all levels. Finally, the greater improvement from simulation (for both rational and small degrees of deviation from rationality) for the TPB than for the MGB for both Intention and Behavior, imply that ABM simulations are more useful for theoretical models that leave a greater proportion of variance unexplained to start with.

Overall, the results of this initial exploratory contribution demonstrated that ABM simulations have the potential to be very useful for understanding and predicting behavior also at the intra-agent level. Especially for the TPB, the agent based approach significantly improves the prediction of the transition from intention to behavior, which is of critical importance in social psychological models (Sheeran, 2002). The introduction of a small degree of deviation from rationality in the decision process illustrates that people do not always act upon their intentions and are not completely rational whereas the increasingly worse results obtained for a greater degree of irrationality also suggests that people do not act too randomly, although occasionally they do so. Nevertheless, these improvements did not systematically occur for the MGB. As hypothesized, the improvement in goodness-of-fit from simulations was inversely proportional to the complexity of the model. In fact, when a model predicts a variable very well, such as the MGB for Intention (67% and 82% for data sets 1 and 2, respectively), there is less utility for simulations and for the

Table 2
Comparison summary results for the Simulation from Data Set 2 on doing vigorous physical activity.

	Behavioral desire				Intention				Behavior			
	Estimated		Simulated		Estimated		Simulated		Estimated		Simulated	
	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*	RMSD	*r*
TPB rational	na	na	na	na	.051	.981	.025 (51%)	*.989.*	.069	.925	.051 (26%)	*.977*
TPB deviation of 5%	na	na	na	na	.051	.981	.027 (47%)	*.991*	.069	.925	.048 (30%)	*.982*
TPB deviation of 10%	na	na	na	na	.051	.981	.031 (39%)	*.989*	.069	.925	.064 (7%)	*.980*
TPB deviation of 20%	na	na	na	na	.051	.981	.050 (2%)	*.982*	.069	.925	.086 (−25%)	*.976*
TPB deviation of 50%	na	na	na	na	.051	.981	.092 (−82%)	*.989*	.069	.925	.163 (−157%)	.972
MGB rational	.042	.982	.074 (−76%)	.981	.042	.979	.080 (−90%)	.967	.070	.926	.080 (−14%)	*.975*
MGB deviation of 5%	.042	.982	.068 (−62%)	*.988*	.042	.979	.076 (−81%)	*.981*	.070	.926	.074 (−6%)	*.973*
MGB deviation of 10%	.042	.982	.083 (−97%)	.979	.042	.979	.105 (−150%)	.958	.070	.926	.079 (−13%)	*.975*
MGB deviation of 20%	.042	.982	.078 (−86%)	*.992*	.042	.979	.110 (−162%)	.969	.070	.926	.087 (−24%)	*.966*
MGB deviation of 50%	.042	.982	.096 (−128%)	.981	.042	.979	.147 (−250%)	.978	.070	.926	.159 (−127%)	*.968*

Note: Percentages of improvement or decrease in fitness in the simulated distribution relative to the estimated distribution are indicated into brackets. The underlined percentages indicate an improvement of the simulation over the estimate. The correlations in italics indicate an improvement of the simulation over the estimate.

effects of deviation from rationality compared to a model such as the TPB that explains substantially less variance to start with (49.7% and 42.3% in Intention for data sets 1 and 2, respectively). An additional aspect of the results supports this hypothesis: compared to the second data set, the parts of variance explained in Behavioral Desire (only MGB), Intention and Behavior in the first data set were lower for both TPB and MGB whereas the improvements from simulations were greater (cf. Tables 1 and 2). Therefore, the improvement in goodness-of-fit from simulations seems inversely proportional to the variance explained by statistical estimations. Moreover, the nature of each of the two data sets is quite different from the other, in the sense that data set 1 is more heterogeneous and noisy, containing more significant outliers than data set 2. This seems to suggest that the usefulness of ABM simulations increases with the heterogeneity of the real data, which are more difficult to analyze using standard statistical techniques. Finally, one could argue that drinking fizzy soft drinks is probably a more automatic and less deliberative or planned behavior, and is therefore less driven by rational considerations compared to undertaking vigorous physical activity. The introduction of a small deviation from rationality is thus more beneficial for the first case than for the second one.

5. Future directions and conclusions

In this paper, we have illustrated the use of ABM simulations in a novel way that allows for the study of intra-individual decision making processes. This contribution is a first step toward simulation based studies, in which higher and lower levels of analysis are combined. Indeed, ABM can provide further new insights by simulating interactions between individuals who will be considered as macro-agents and who will consist of a model of Attitude, Intention and Behavior, as we have used in this study. One could test, for instance, which construct has more influence or examine whether all constructs change in a threshold-like or continuous manner (Urbig, 2003). One could also introduce other factors such as personality dimensions to see whether they could help to reduce further the intention–behavior gap without the need to collect real data for each and every newly introduced feature. Indeed, one of the advantages of ABM is that any theoretically plausible factor can be added to a model and simulated to see whether it affects the outcome. One can subsequently test whether the key insights provided by the simulations are actually verified empirically in laboratory settings or in field studies. Moreover, a step-by-step testing approach is the preferred option when developing ABM simulations, in order to better understand and predict behavior.

In conclusion, this contribution has shown that ABM generally allows for a more realistic modeling of human decision making processes. Future studies can build on these initial results and introduce additional elements, including interpersonal and social influences that should lead to a better prediction and understanding of socially relevant behavior in meaningful situational contexts. Moreover, as argued by Smith and Conrey (2007), the adoption of an ABM approach in social psychology can allow a more fruitful integration with results and insights from other scientific disciplines, where the use of dynamic simulation approaches is already well-established.

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