Special Feature

Behavior Analytics, Artificial Intelligence and Digital Technologies

Building bridges between biological, social and food systems

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Key messages

> The complexity of obesogenic behaviors, and especially eating behavior, is related to its multiple contextual and individual determinants.

> Large-scale data on human behavior is becoming more available, opening new perspectives on bridging biological, social and food environments.

> The integration of consumer insights and behavioral economics may help in the design and deployment of interventions targeting lifelong nutrition, health and wellness in a manner that is also economically, culturally and environmentally sustainable.

> New digital methods of behavior analytics that integrate large-scale data offer opportunities to more deeply comprehend underlying behavioral patterns and their relationship to biological, social and food systems.

Introduction

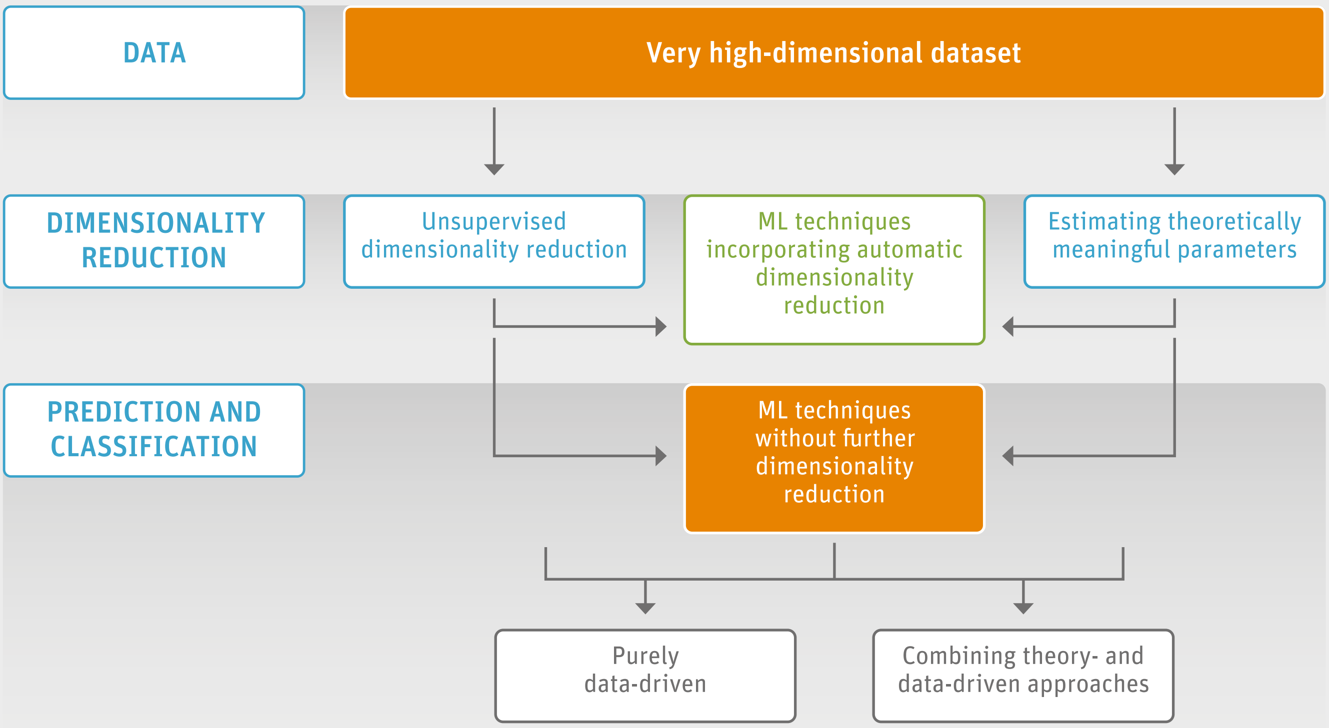
Diet-related diseases, be they tied to undernutrition or obesity, remain one of the most pressing societal challenges.[1] In Canada, over 60 percent of the adult population is overweight or obese.[2] Excess body weight is a significant risk factor for several diseases including heart disease and cancer, which are the top causes of death in North America.[3] Alarmingly, life expectancy in the USA has decreased for 2 years in a row, partly due to diet-related chronic diseases and overweight/obesity.[4]

Meanwhile, India is the 'world capital' for undernutrition as well as diabetes – a chronic disease largely tied to overnutrition.[5] These figures highlight the urgency for more effective strategies to support both individuals and families in their struggle for lifelong nutrition, and also to assist those actors throughout society that define contexts for food choice and behavior.

"The most modern methods of consumer insights are increasingly informing interventions that target health-promoting dietary behavior"

The most modern methods of consumer insights, behavioral economic nudges and other theory-based behavioral assessment and change strategies are increasingly informing interventions that target health-promoting dietary behavior.[6] These tools hold high promise for improved targeting, with a stronger and more

FIGURE 1: Machine learning (ML): the identification of descriptors based on objective computational functional variables



Adapted from Huys, et al. 2016[12]

lasting impact. Consumer insights, for instance, provide information on the diverse drivers of behavior in different populations and/or in the same individual in different situations or over time.[7] These are typically combined with the mapping of consumer journeys, an approach that typifies behavioral economics methods designed to acquire a 360° view of how specific foods fit within specific types of eating episodes, and how these episodes accumulate into a person's diet as part of their livelihood, lifestyle, social life and cultural values. Consumer insights also explore how nutrition and health are positioned in relation to other motives such as taste, fun, convenience and price. In commercial contexts, consumer insights also specify all points of value creation along the full experience of shopping, purchasing, preparing, consuming and disposing of food products.[8,9] The loyalty and relationship management programs of manufacturers and/or retailers encourage the repetition of such cycles and provide opportunities for the assessment of long-term patterns and outcomes.

In addition, the integration of consumer insights and behavioral economics may help in the design and deployment of interventions that target lifelong nutrition, health and wellness in a manner that is also economically, culturally and environmentally sustainable.[10,11] This is particularly the case considering the richness of data on both real-world behaviors and real-world contexts that is produced in real time with the ever-increasing and ever-faster digitization of everyday life, economy and society, combined with the power of advanced analytics and artificial intelligence (AI).

This digital transformation is happening not only in industrialized countries but also in still-traditional contexts around the world as they open up to modernization. Digital tools, some of them powered by AI, are now available to support individuals and families in their daily quest for a healthy diet, whether this involves assembling a portfolio of commercial food, homegrown products, or a combination of both. In this paper, we first present a general framework for behavioral analytics, then explain how behavioral insights can be derived from such information, and how predictive and other models can be used to inform dietary choice and, in some cases, to monitor long-term outcomes. We then outline what could be the next generation of decision support that would assist not only individuals but also decision-making by all actors throughout society that are involved in defining the context in which a person's dietary behavior is performed.

General framework for behavioral analytics

Before addressing the content aspects of AI-powered behavioral analytics for life-course nutrition and health, we first offer a general approach adapted from medical data science to extract theoretically informed insights from big data and digital technologies.[12] This approach aims not only to characterize differentiated behavioral patterns and/or to predict outcomes, but also to trace underlying mechanisms that may be intervened upon (see **Figure 1**). The approach illustrated in **Figure 1** entails **(1)** behavioral performance of serious gaming tasks that index various neurophysiological and/or psychological processes; **(2)** computational models that identify the generative psychological processes; **(3)** parameter-estimation methods to quantitatively fit these models to individual behavior by hierarchical Bayesian estimation and **(4)** machine-learning clustering methods to identify key contextual/task conditions and individuals within subgroups. 'Machine learning' refers to data-driven, theory-agnostic methods that perform dimensionality reduction in order to extract core mechanisms before performing classification or regression so as to identify descriptors based on objective computational functional variables (**Figure 1**).

> "This approach aims to trace underlying mechanisms that may be intervened upon"

Moving to the behavioral analytics framework (**Figure 2**), it is now possible to capture behavior (e.g., exercise activity, eating habits and health metrics) at an unprecedented level of granularity that was not directly observable at such scale only a short time ago.[13] This may be in terms of behavioral components along the consumer journey or else in terms of influences at different temporal or geographical scales that define choice contexts.[14] The domains of food, nutrition and diet have seen the proliferation of apps to support the consumer; these range from shopping aid, through consumption record, to goal setting and monitoring, and are often combined with wearable technologies. The richness of data then allows for the development of health nudges or other interventions, such as using social settings to motivate individuals to adopt healthier lifestyles. For example, recent consumer research shows that users of Fitbit (one of the most popular apps in North America) exercise more if their network of friends also exercises more, compounding the positive effect of the digital support per se.[15] These studies provide the first glimpse about the possibility of leveraging big data in developing healthful nudges.

The second use of big data is for predictive analytics to generate new datasets that would otherwise not exist.[16] Given the wealth of data from the internet, technologies now exist to extract information from unstructured data (e.g., text, images). In fact, research study platforms such as Ethica.com now allow researchers to collect textual and visual information from experiment participants. The analysis of this new type of data is made possible by virtue of the recent advances in machine learning. Recent consumer data science research demonstrates the use of deep learning to help categorize pictures posted on social media platforms such as Instagram.[17] As posting pictures of meals and/or food is becoming increasingly common, this new data can be used to assess (in great detail) the types of food individuals are consuming. Text is another major source of unstructured

FIGURE 2: Behavior analytic framework

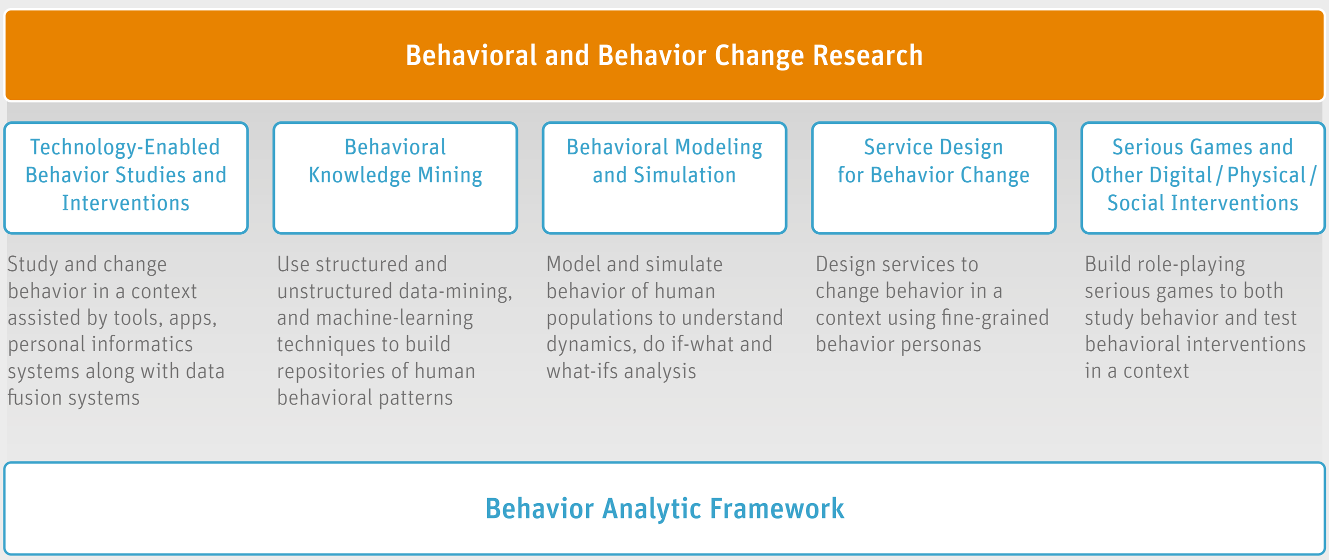
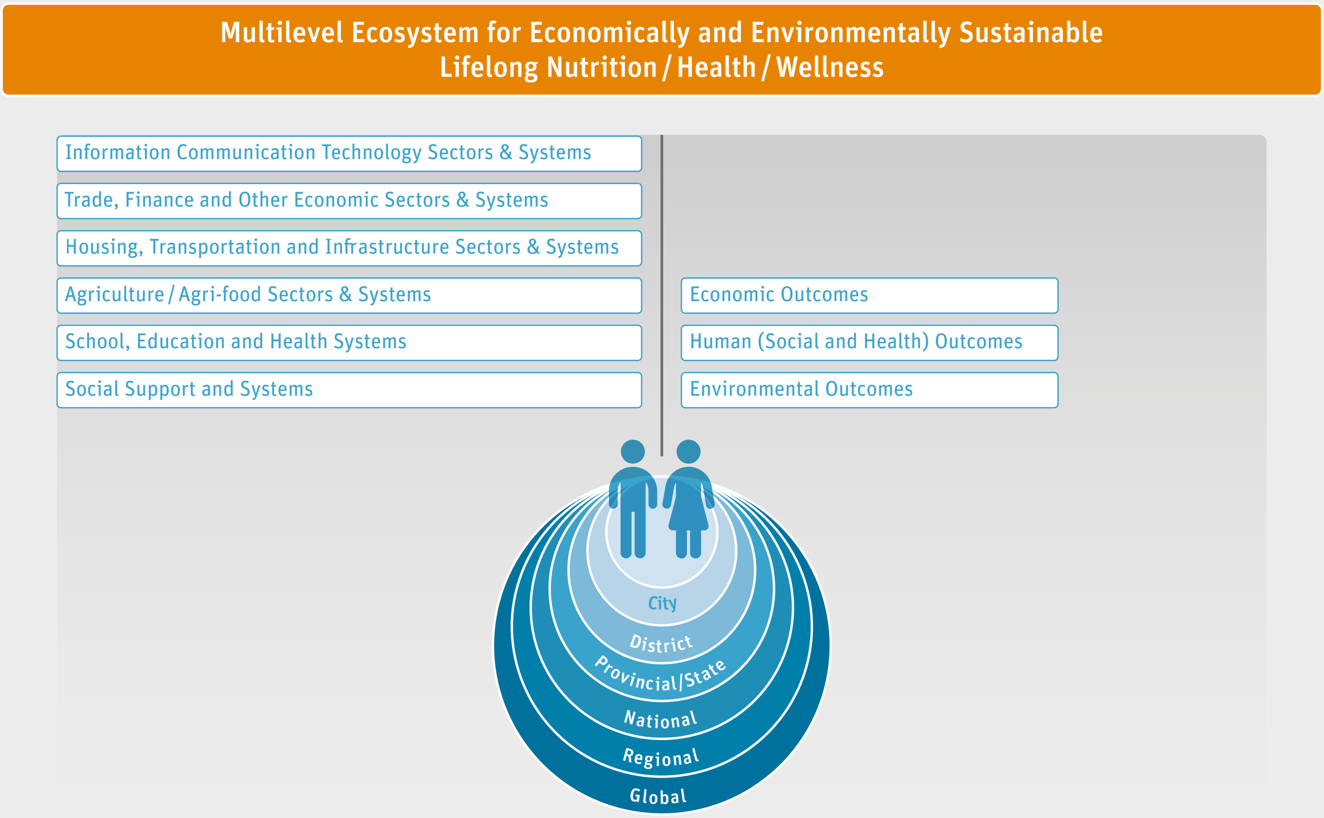


FIGURE 3: Person-centered ecosystem



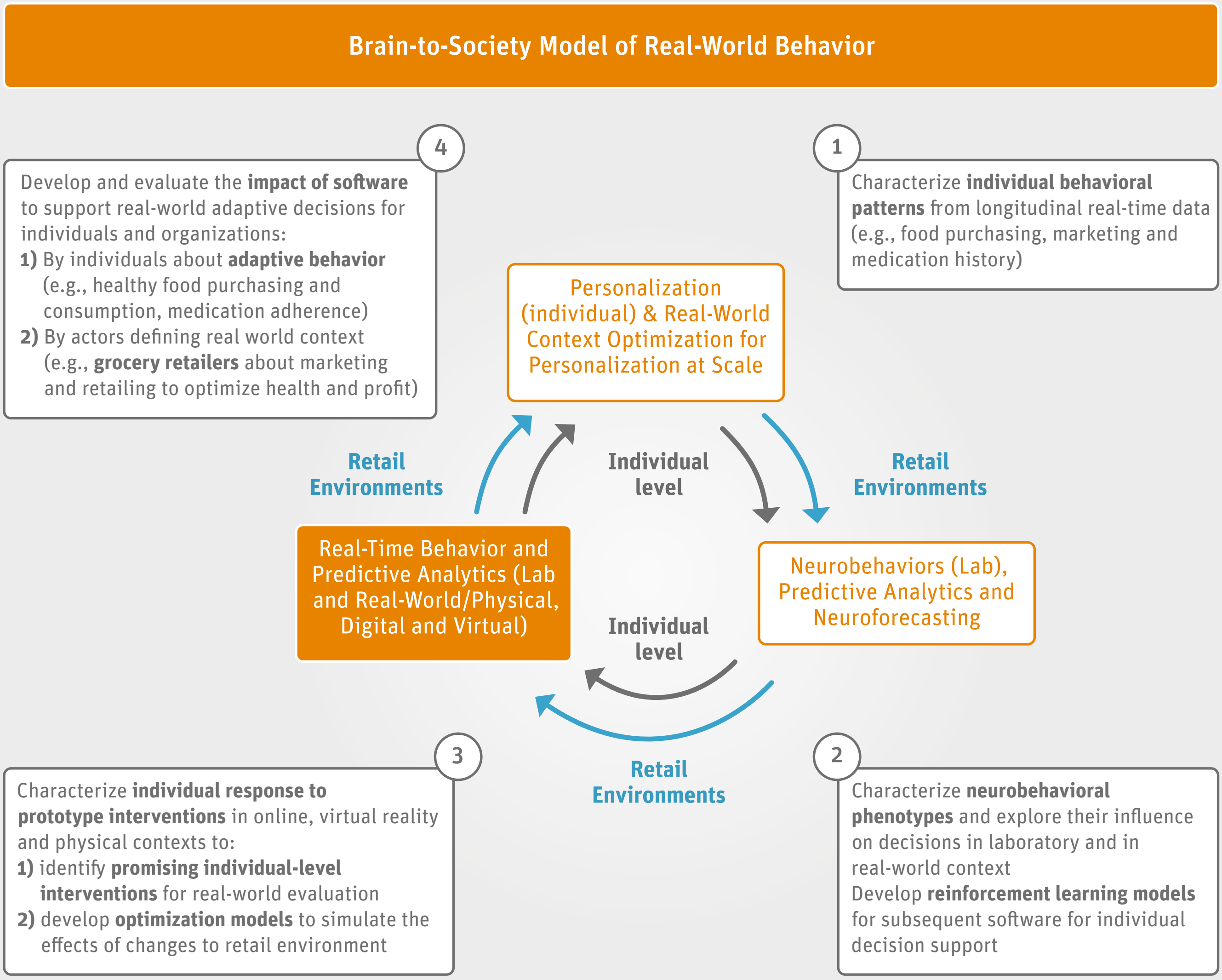
data, and natural language processing has allowed researchers to extract important features from this data. For example, fitness and food trackers are essentially modernized food diaries. Consequently, the ability to process, synthesize and categorize large bodies of text at scale means that these new technologies can be used to convert food diary information into data formats that are conducive to further analysis (i.e., what foods people eat together at the same eating episode).

> "The new technologies can be used to convert food diary information into data formats that are conducive to further analysis"

A third use of big data and AI for deriving behavioral insight is to unravel mechanisms and establish causality whenever possible for individuals themselves, and/or in terms of the combined contribution of the complex and dynamic web of biological, social and system-level factors impacting a person's dietary behavior at any time. Such knowledge is necessary in order to know what works, for whom, when and in what contexts, and also to inform the design of well-targeted nudges or any other innovation/interventions targeting improved nutrition and health. This ensures that the interventions work when they are expected to. Machine learning and AI have helped improve the credibility of causal inferences. For example, an increasingly popular method for causal inference makes use of random decision forests to obtain treatment effects that are heterogeneous across individuals.[18] The ability to obtain heterogeneous effects will allow for better personalization of health nudges, as each individual (or population segment) will likely respond to the proposed behavioral interventions in a different manner in different contexts.

Digital synthetic ecosystems are added to the portfolio of behavior analytics for their ability to position individuals (or, rather, statistically representative units of a given population) within the complex and dynamic contextual conditions impacting behavior at any point in time and over a person's life-course. As illustrated in **Figure 3**, these ecosystems are tied to multiple sectors and multiple scales and jurisdictions. Using systems science approaches, researchers can visualize scenarios that cannot be carried out in real populations or for which adequate historical data on natural experiments are not

FIGURE 4: Behavior analytics for 21st-century research and action for lifelong dietary behavior



available. Computational models can now be developed to capture some of this complexity, but these must be both theoretically grounded and empirically informed. In this context, we are developing for the City of Montreal a SynthEco platform for creating synthetic ecosystems, which are a virtual platform to make statistically representative synthetic populations and environments and simulate the impact of different intervention prototypes over time. This is achieved through the compilation and statistical extrapolation of various disparate data collection efforts (census, cohorts, clinical studies and diverse surveillance data) into a population-level, geographically explicit representation, so as to operationalize government, private and academic research for population-level planning. Traditionally, synthetic ecosystems have served as the basis for agent-based simulation in infectious disease and public health modeling, as well as transport modeling.[19–22] Synthetic Ecosystems give researchers the ability to map cohort and cross-sectional data collection efforts, environmental surveys and geospatial information in a common environment in order to represent a diversity of indicators and population characteristics. They can be a powerful support for academic, private and public research, action and monitoring (Figure 3).

Finally, behavior analytics, AI and digital technologies can inform the design of theory-informed and evidence-based health-promoting food/nutrition/health innovations and/or any type of interventions, be these of a digital, social or physical nature. For instance, digital monitoring tools and serious games can support self-regulation.[23] Serious games are digital platforms that combine game technology and game-based methods and concepts with further technologies and research disciplines such as ICT, digital media, sensor technology, psychology, pedagogy and sports science and apply them to different application domains, including health, persuasive games, advergames and games for education and training of differing complexity.[24] As another example, large-scale data can assist in the development of gamification/goal design for healthy nudges, as shown by a large-scale study about millions of mobile users of Lose It – another popular app supporting healthy diet and lifestyle, with the primary goal of weight management.

> "Behavior analytics, AI and digital technologies can inform the design of health-promoting food/nutrition/health innovations and interventions"

A framework for 21st-century research and action

In conclusion, as illustrated in **Figure 4**, data and digital tools can be embedded within physical and social laboratories as well as real-world contexts. Taking an adaptive learning approach that combines research and action in a novel way, a brain-to-society approach to behavioral analytics includes cycles of controlled and real-world exploration to account for the whole sequence of biology-brain-technology-society factors acting upon the real-world dietary behavior both of individuals and of populations, in real time and over the life-course. Challenges and possibilities are high and call for a constant consideration of ethical and moral principles, balancing access to an unprecedented richness of evidence against privacy concerns. As we enter the fourth Industrial Revolution, which blurs the boundaries between the biological, physical and digital realms, we believe that behavioral analytics, AI and digital technologies can help in accelerating societal-scale solutions in ways that were never previously possible.

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