

A Network View of Human Ingestion and Health: Instrumental Artificial Intelligence

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Abstract

Humans are confronted with an increasingly complex array of ingestion substances and dietary choices that influence health and well being. However, even with strong medical evidence that clearly links ingestion strategies and health consequences, the general public struggles to make health-optimizing ingestion decisions. Based on our literature review, we delineate a typology of barriers to formulating health-optimizing ingestion strategies. We propose that the introduction of artificial intelligence (AI) as “decision management” (AI-DM) technology into the ingestion decision-making network would increase the likelihood of more predictable and optimized health outcomes. Also, we delineate the key informational constituencies needed to enable a comprehensive and effective AI-DM system. While no author has yet proposed AI in the particular context discussed in this paper, the theoretical and empirical literature suggests that this might be possible. We conclude by discussing areas for additional research.

The Ingestion Challenge

Humans are confronted with an increasingly complex array of ingestion substances (e.g., natural foods, processed foods, pharmaceuticals, recreational drugs, and toxins) and dietary choices that influence health and well being. While more scientific information about the health implications of particular substances intended for human ingestion has become available in recent years, a typical consumer’s potential to carefully analyze this disclosed information, understand possible interactions between substances, and reach individualized health-optimizing decisions may be limited by a variety of factors. For example, an individual’s cognitive capacities (as with children and Alzheimer patients) and the complexity of the decision environment are critical moderating and mediating variables (Gonzalez, Thomas, and Vanyukov 2005).

Information for many substances may not be complete or “perfect” and may contain perceived contradictions that contribute to sub-optimized decisions. Also, a particular person’s health situation (e.g., genetic, illnesses, and health risks) and diverse contextual factors (e.g., climate and socio-economic situation) add complexity and make the decision environment dynamic.

This interdisciplinary paper reviews medical, health, innovation management, legal, and artificial intelligence (AI) literature with the overarching aim of answering the following questions: *Would artificial intelligence as an intervention help to optimize ingestion decisions? Could artificial intelligence be instrumental in assisting humans with complex ingestion decisions? Given our current understanding of ingestion substances and their interactions, which AI methods might deliver the most reliable assistance?* Our research-framing paper describes human ingestion challenges and uses Latour’s (1991) actor network theory (ANT) lens to explore potential solutions derived from the AI literature.

Substances and Interactions

While many medical and health scholars have identified the various challenges associated with human ingestion, few have offered solutions. Amft and Tröster (2008) have identified dietary imbalance as a factor contributing to chronic diseases. Petot, Marling, and Sterling (1998) describe the challenges associated with optimal menu planning. Brand-Miller et al. (2009) demonstrate that dietary strategies are critical for managing health and preventing diseases. Pharmaceutical firms and researchers give scientific evidence of various drug-drug, drug-food, and drug-herb interactions and suggest drug intake coordination approaches (Abbott 2011; Bailie et al. 2004; Kuhn 2007; PDR 2008; Zuccherro, Hogan, and Sommer 2004). Furthermore, interactions are often classified as either pharmacodynamic, interactions among concomitant drugs, or pharmacokinetic, interactions arising from

metabolic action in human bodies (Bailie et al. 2004; Zuccherro, Hogan, and Sommer 2004). Other researchers indicate the importance of contextual factors as mediators of health outcomes (Trinh-Shevrin, Islam, and Rey 2009).

However, even with strong medical evidence that clearly links ingestion strategies and health consequences, the general public struggles to make health-optimizing ingestion decisions. Despite increased labeling and disclosure requirements for food substances, Andrews, Netemeyer, and Burton's (2009) empirical study reveals a curvilinear relationship between ingestion knowledge (e.g., disclosed caloric information, health consequences, and motivation to search for nutrition information) and intent to purchase high-calorie foods. They write:

In our ad-based research, reader-response interviews suggest that relative nutrition claims can create a positive "halo effect." They can also lead to a reduced likelihood of perceived weight gain risk, which in turn increases the intention to buy food that is not viewed as particularly healthy. (Andrews, Netemeyer, and Burton 2009: 51)

Maffei and Pinelli (2008) have identified the need for behavioral based "nutritional" interventions to assist diabetic children with ingestion choices. In addition, Okonkwo et al. (2008) has studied cognitive impairment, such as Alzheimer's disease, as a predictor of sub-optimal decision-making. The growing body of medical and health literature suggests that the increasing array of ingestion choices and other factors pose challenges to consumers when attempting to optimal health outcomes. Ingestion decisions become especially difficult when the positive and negative effects of interactions are considered. For example, pharmaceutical producers recommend that users who ingest synthetic forms of thyroxine (thyroid hormone), due to reduced thyroid activity and levels in the body, should consider the negative interactions that such pharmaceuticals have with various other substances (Abbott 2011). These users are advised to not ingest calcium during a six to eight hour window of taking synthetic thyroxine (Abbott 2011). Furthermore, they are advised to ingest this pharmaceutical drug during the morning after awakening. However, an investigation of common breakfast foods and supplements such as yogurt, oatmeal, and multi-vitamins reveals that they contain varying amounts of calcium. This complicates the ingestion decision-making process and demands more sophisticated ingestion strategies if individuals want to optimize health outcomes.

Barriers Typology

Based on our review of the literature, we have delineated a typology of barriers to formulating health-optimizing ingestion strategies as follows:

- **Information availability:** *Is information about substances, various interactions with other substances, and human health implications available? Is information about individuals including health conditions available? Which types of data (see Figure 1 below) are available? How do regulatory regimes impact the availability of information?*
- **Information quality:** *Can the quality of information be assessed or known? Is the information about a substance consistent across multiple sources? Are information sources known and validated (e.g., expert, user curator, or peer-reviewed)?*
- **Information medium:** *Is the information in a form that would allow for transmission via digital means? Which particular medium (media) and technology platform(s) might be most usable?*
- **Information harmonization:** *Is the information from various sources universally formatted? Can the information from various sources be harmonized?*
- **Information mutability:** *In what ways is information about substances and individuals likely to change and likely to become available? Is the temporal pace of change known or knowable?*
- **Cognitive sense-making capacity:** *To which degrees are individuals able to collect, understand, and interpret information about substances?*
- **Cognitive in situ decision-making capacity:** *To which degrees do individuals have an ability to decide in situ and take a course of action based on information about selves and ingestion substances?*
- **Behavioral change capacity:** *To which degrees do individuals have the ability to change ingestion behaviors?*

Instrumental AI, Decision Management

Applying an ANT approach, we propose that the introduction of additional technological actants into the ingestion decision-making network (i.e., chain) would increase the likelihood of more predictable and optimized health outcomes. We refer to this addition of AI as "decision management" (AI-DM) technology. Currently, most consumers use disclosed or secondary research information to formulate ingestion decisions then ingest particular substances such as food and drugs.

Using the Latourian designations "H" to refer to human actors and "NH" to designate non-human or technological actants (Latour 1991: 110), we describe a typical ingestion decision-making network with the following scenario:

H_D (number of humans desiring improved health)
 $+ NH_I$ (ingestion information about substances and self)
 $+ NH_S$ (ingested substances)
 $= H_W$ (number of humans with improved health)

This may be expressed as:

$$H_D + NH_I + NH_S = H_W$$

After the introduction of instrumental AI into our network, the following revised scenario emerges:

H_D (number of humans desiring improved health)
 $+ NH_I$ (ingestion information about substances and self)
 $+ NH_{AI-DM}$ (**AI-DM for ingestion decisions**)
 $+ NH_S$ (ingested substances)
 $= H_{WX}$ (number of humans with improved health)

This new scenario may be expressed as:

$$H_D + NH_I + NH_{AI-DM} + NH_S = H_{WX}$$

We posit that the revised scenario, when compared to the original, would yield a greater number of humans that experience improved health. Therefore, theoretically it would seem that AI technology could be instrumental in assisting with the information collection, processing, and decision-making challenges described above. For example, AI, applied through various fixed and mobile devices (e.g., smart phones and personal computers), could be used to analyze the dietary information of a multi-substance palate option to determine both the direct and interactive implications and, thus, predict the likely health outcomes if ingested. Actual substances or prepared information about substances could be scanned in situ to determine individual dietary information and the interactive effects of multi-substance combinations, such as food and medicine. AI could further analyze the implications of these substances and be used to create optimal ingestion strategies. For example, AI could set eating schedules and generate “intelligent” menus to minimize negative interactions between certain medicines and foods. Furthermore, AI could help discern negative intra-food interactions that might be found in multi-component food assemblies such as the ubiquitous cheese burger or pizza.

An effective AI-DM system would need informational inputs from a variety of constituencies. Flowing from our discussion of barriers above, we delineate the key informational constituencies in Figure 1. An AI-DM system would effectively act to make information symmetrical among these stakeholders. For example, producers of all types of ingestion substances (e.g., food, pharmaceuticals, and supplements) would need to contribute substance-specific information. Medical and health researchers and professionals would need to contribute information about humans and health.

Technology researchers would contribute information about health care and treatment technologies. Individual consumers or users would need to disclose presumably secured information such as medical records and drug regimens supplied by medical and health professionals. Secondary constituencies might include producers and researchers responsible for other environmental or contextual factors. For example, building researchers might contribute information about the effects of temperature, lights, air quality, etc. on human ingestion processes. Government regulators or standard setting organizations might contribute diverse incentives and develop harmonized information standards. Law makers might also help refine data privacy standards to enable the system to function. Testing groups would contribute independent efficacy testing that would aid AI-DM developers (Garud and Karnøe 2003). Lastly, AI researchers and developers need to contribute the central mechanisms that enable the entire system.

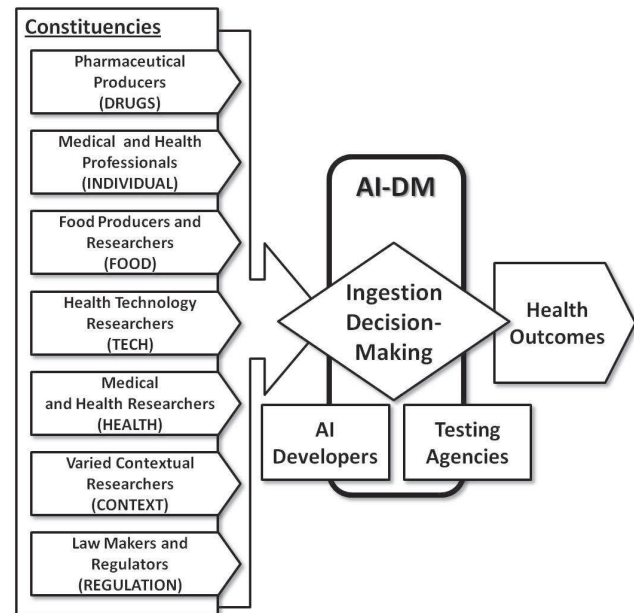


Figure 1, Conceptual Model with Information Constituencies

However, is there existing evidence that artificial intelligence might be instrumental in assisting humans with complex ingestion decisions by overcoming the obstacles proposed above? While no author has yet proposed AI in the particular context discussed in this paper, the theoretical and empirical literature suggests that this might be possible. Fleming, van der Merwe, and McFerren (2007) demonstrate the usefulness of AI when processing complex and mutable health information. Cortes et al. (2000) identified instrumental forms of AI that might assist with Environmental Decision Support Systems (EDSS)

designed to augment human cognitive capacities when tasked with assessing information about the natural environment. They suggest that certain forms of AI could aid with obstacles such as large and complex information sets of uncertain quality. O'Hare et al. (2007) demonstrate how AI becomes instrumental for in situ decision making when deployed through distributed sensing devices and networks. Liu and Yu (2009) propose a system that utilizes two forms of AI, case-based reasoning (CBR) and fuzzy reasoning (FR), for enhanced risk forecasting and management.

Papers by both Goyache et al. (2001) and Marini (2009) study AI applied to food substances. Goyache et al. advocate for AI as an instrument to assess quality and other aspects of food products. Marini's work is especially useful for AI-DM since it gives a detailed explanation of artificial neural networks (ANN) used in food analysis. He speculates that future ANN will be developed for deployment in chemometric fields (Brereton 2009) and modified by the use of class-modeling algorithms and multi-dimensional pattern recognition. He notes that the latter, for example, would help with authentication of various aspects of food such as chemical composition (Bosque-Sendra, Bro, and Cuadros-Rodríguez 2011; Feudo et al. 2011), origin, and informational labeling.

For an ANN-based comparative model, AI-DM developers might refer to computerized clinical decision support systems (CDSSs). Garg et al.'s (2005) empirical meta-analysis revealed that CDSSs improved practitioner performance in 64% of the reviewed studies. Other similar research (Jaspers et al. 2011; Robertson et al. 2010) indicates that both practitioners and patients benefit from the deployment of CDSSs.

Conclusion

We conclude by highlighting areas for additional research. Although our initial review of the literature suggests that AI could instrumentally mediate health outcomes, many questions remain, especially in the social realm. In addition to the direct informational and cognitive challenges outlined above, other stakeholder difficulties may emerge. Network density, as defined in network theory, suggests that all information constituencies must actively participate if an AI-DM system enabled network is to provide high value (Onnela et al. 2007). Yet we can imagine that certain stakeholder groups might be reluctant to contribute. Food producers with a short-term view might determine that current informational asymmetries are more financially rewarding than an uncertain future with greater informational costs and more information-empowered and discerning consumers. Accordingly, these producers might not contribute to an AI-DM enabled network.

To mitigate this challenge, greater regulation or incentives might be needed if an AI-DM system is to be broadly deployed. Governments have historically been interested in the ingestion decisions and behaviors of its citizens. For example, the United States created the Food and Drug Administration (FDA) in response to food adulteration and misbranding. The FDA has developed various labeling regimes for food products reflecting various social goal such as improving human health and safety, mitigating environmental hazards, averting international trade disputes, and supporting domestic agricultural and food manufacturing industries (Golan et al. 2001). Weil et al. (2006) summarize the underlying policy rationale for labeling regimes as follows:

The rationale for government intervention starts with the premise that information asymmetries in market or political processes obstruct progress toward specific policy objectives. Asymmetries arise because manufacturers, service providers, and government agencies have exclusive access to information about products and practices and they often have compelling reasons to keep that information confidential. (Weil et al. 2006: 156)

Besides regulatory mandates to disclose information about food products on nutrition labels, food producers have their own incentives to share information about the ingredients of their products if doing so can help to distinguish them from their competition (Golan et al. 2001). However, as the quote above suggests, firms frequently have incentives to hide information about the health attributes of their products. In the absence of regulation, producers will often abstain from sharing information with the market.

Equally challenging, certain consumers may be reluctant to use an AI-DM device or incapable of adopting its suggested behaviors. User acceptance might be enhanced if developers considered lifestyle factors such as affordability and accessibility of food products, ease of food preparation, and culinary tastes.

Lastly, more research on the algorithmic underpinnings and limitations of current AI technology is necessary (Coghill, Srinivasan, and King 2008; Huang, Jennings, and Fox 1995; Park and Darwiche 2004). Also, more cross disciplinary research from the food chemistry, the medical, and the public policy and economics realms would be useful. More information about potential devices, available data sets, and privacy restrictions on the use of data is needed. Although the problem and challenges described above are formidable, we believe that an AI-DM system innovation would yield social benefits by significantly sustaining human life spans and enhancing life quality.

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