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Mind, Consumers, and Dairy: Applying Artificial Intelligence, Mind Genomics, and Predictive Viewpoint Typing

*Ryan Zemel, Somsubhra Gan Choudhuri, Attila Gere,
Himanshu Upreti, Yehoshua Deite, Petraq Papajorgji
and Howard Moskowitz*

Abstract

We present a new approach to more deeply understand the mind of consumers with respect to food products, using a combination of artificial intelligence to provide the ideas, Mind Genomics to understand how consumers respond to these ideas, uncovering Mind-Sets, and statistical assignment of new people to these newly uncovered Mind-Sets using the PVI, personal viewpoint identifier. We illustrate the approach in detail with yogurt, and then present data from other studies about yogurt, milk, and cheese, to reveal new knowledge about emergent Mind-Sets for conventional dairy products. The key benefits of the approach are the scope (many ideas from artificial intelligence), discipline (experimental design to uncover what is important), actionability findings, mind-types, speed (within 2 or 3 days), and cost (low because of automation).

Keywords: consumer, conjoint analysis, e-commerce, product development

1. Introduction: the Big Data or fire hose of information

Our twenty-first century world is awash with information. One need only look at the amount of information on the Internet about any topic, and the likelihood is that the number of sites is in the tens of thousands, if not more, at least for topics which are popular. It is not the lack of information which is the bane of our century, but the plethora, metaphorically the fire hose of information.

Our thinking to deal with such an abundance of information is either to shut out most of it, or do some type of directed search for the topic. One cannot absorb the totality of information in a popular subject, nor perhaps even form a reasonable opinion based upon deep knowledge, unless perhaps one has specialized in the topic and has amassed a great deal of information after years of practice. There are of course tools which sift ideas, such as Google® for conventional websites, and Google Scholar® for academic papers. These sifting tools aggregate data “on the fly,” presenting the raw material as different sites to explore. One can then use the

Google® tools to get a sense of what is “au courant,” although the effort to do so may be more daunting in the execution than in the expectations before the effort is made.

With the foregoing introduction, the next question is how does the novice, whether scientist or simply interested layman, learn about the mind of a consumer toward a specific product? For instance, let the product be “milk.” A Google® search of consumer + milk shows a mere 130 million sites. Refining the focus for Consumer Attitudes Regarding Milk, again on Google® revealed 6,280,000 hits. A more focused search, this time for academic papers, on Google Scholar®, for Consumer Attitudes Towards Milk, revealed 90,700 hits. Certainly, enough for a number of PhDs, and for a lifetime of reading, but what about the practical problem of the small, even a start-up company, wanting to develop a new product? The “plethora of choice” in the world of information is simply paralyzing, so that the expeditious answer is to guess, to solicit the advice of an expert, to buy a book of trends in food, to run a focus group, or perhaps to spend a great deal of money developing products and concepts with the full confidence that it **MUST BE GOOD** [1, 2].

Whether the foregoing picture presents a positive development, a negative development, or perhaps just a development without valence is not the issue. The issue for this chapter is whether one can use the mass of information to understand issues, say in dairy, with these issues relating to the attitudes of consumers. Simply stated, can we create a system to rapidly and profoundly understand the mind of the consumer regarding a specific topic, and, where possible, incorporate the contribution of the “Big Data of Relevant Information?”

2. Surveys, observations, and their limits

For a century now, the norm for understanding subjective reactions to products has been to ask people to talk about these products in focus groups or other qualitative methods [3], and for those who are quantitatively oriented, to ask questions of people in a survey. Often surveys begin with topics about what one does in general, such as food preferences and food habits [4], now evolving down to a momentary survey after a relevant experience to ask ‘How did we do?, or ‘Would you recommend us to someone with whom you do business?’ the now-ubiquitous NPS, (Net Promoter Score), analyzed by [5].

As the amount of information increases, and as companies run surveys about the attitudes and usages of product, whether dairy or other food products, it is becoming increasingly obvious that data are cheap to obtain, but true knowledge of the so-called actionable nature is expensive. By actionable, we mean the use of the data to effect some change, whether that be convincing someone to try or buy a product, or learning how to change the ingredients of a product to increase acceptance. Surveys are limited to the respondent’s conscious efforts to answer the interviewer’s questions. Often, they require knowledge to which the respondent may not be privy, or may require “politically correct” answers. An example of the former, information to which the respondent is not privy, is what to do to change the fat content of milk, or to make the milk taste like it is full fat. The latter, “politically correct” answers come from the desire to give the correct or socially approved answer. For example, a person who loves whipped cream in great amount on cake as a delicious dessert may simply not describe dessert preferences, or when doing so may consciously or perhaps even unconsciously forget one’s lifelong obsession with mountains of whipped cream when allowed to consume it.

3. Changing the paradigm from Big Data and surveys to small experiments

The sheer abundance of data, this so-called “hydrant effect” may seduce one into thinking that the “answers are there” but the reality is that one learns far more from simple experiments. In recent years, author HRM has introduced the new, now more rapidly emergent science of Mind Genomics [6, 7]. The name Mind Genomics is metaphorical. It posits that knowledge about decision-making comes from presenting people with combinations of ideas of different types, measuring their responses, and determining which ideas or sets of ideas (mind-genomes) drive the decision-making. To further the metaphor, each topic area of experience comprises a variety of aspects. The aspects of a topic to which a person attends while making a decision are the so-called “mind genomes.” Furthermore, each topic area has a limited set of these mind-genomes, almost mind-alleles, in some sense.

Mind Genomics has already been applied to the dairy world in a number of different, easy-to-do experiments. For example, one study looked at the different ways of making a decision about what a dairy product (yogurt) is worth. Through the Mind Genomics method, it became possible to extract various mind-genomes about yogurt, with each person embodying one of a set of mutually exclusive genomes. The objective of that study was to identify a group of individuals who valued texture or mouthfeel as the basic criterion for decision-making [8].

Other studies of dairy have involved products such as milk, yogurt, cheese and so forth.

4. Positives and negatives of experiments to understand the consumer mind toward dairy

We live in an age of instant gratification, of superficial thinking, of information abundance, and most sadly, a belief that whatever we do has to be made simple, dumbed down. When our focus is to understand the mind of the consumer toward a dairy product, this might mean running a few focus groups to get a “sense” of today’s customer, or doing a general survey about dairy using any of the widely available survey platforms like Survey Monkey® [9]. One could also mine the Web for information, and produce a summarized report of trends. The aforementioned approach provides a great deal of information, often delightfully presented in newsletters, at conferences, at webinars. Yet, there is something missing, the translation of the information into product concepts.

One of the most common, traditional methods of using the data is to present the information from these surveys, focus groups, and so forth to the agency and marketing professionals, often called “creatives.” It becomes the job of the creative to synthesize the information, and with her or his skill, experience, and insight, to emerge with the final “idea,” whether the idea be fully formed or even modestly sketched out.

We are accustomed to experiments in the world of physical features. These experiments may range from a simple change in a product, and the measurement of the consumer response to the product (so-called “cook and look”), all the way up to DOE, Design of Experiment [10]. DOE specifies different combinations of ingredients, and then measures the response to the combination in order to identify what each product ingredient contributes, and how a specific combination performs in a consumer test. DOE is usually in the purview of R&D, and represents a dramatic investment of time and money, but also an increase in the opportunity for a corporate success.

We deal in this chapter with consumer knowledge, ideas. How does one experiment with ideas about dairy? The answer to this question is quite simple. One can present ideas, simple or compound, about a dairy product, and obtain ratings about the ideas. **Figure 1** shows an example of three advertisements about yogurt from Chobani®, presented in the original language, and deconstructed as a preparation for analysis by experimental design:

The choice of concepts in **Figure 1** is simply that. The reasons behind the choice must be left to probing questions asked of those who evaluated the concepts, and/or left to the talented researcher who can “connect the dots” and tell an engaging, and possibly insightful story.

A better way to understand the world of dairy from the mind of the consumer involves experimentation, preferably easy, fast, and inexpensive experimentation that anyone can do [11]. We illustrate the strategy with data from a study

Original ad #1:

Strawberries, plump little hearts grown full and tender, red-ripe and ready-to-love, hidden beneath thick, delicious Chobani® Greek Yogurt.

Mind Genomics format:

Strawberry
Plump little hearts grown full and tender
Red-ripe and ready-to-love
Delicious Greek Yogurt

Original Chobani® ad #2:

New yogurt crunch, milkshakes, and tubes in 11 fun flavors with twice the protein* and nothing artificial

Mind Genomics format:

New yogurt crunch
Milkshake
Fun flavors with twice the protein
No artificial ingredients

Original Chobani® ad #3

Real key lime, ripe and riotous, sweetened and blended in soft, delectable Chobani® Greek Yogurt.

Mind Genomics format:

Real key lime
Sweetened
Soft, delectable texture
Greek yogurt

Figure 1.

Comparison of three text advertisements for Chobani® yogurt taken from the Web (December, 2018), and their deconstruction for study by experimental design (Mind Genomics).

Step	Activity	Rationale
1	Identify the topic	The topic may be product, service, or literally anything where human experience and judgment play a key role.
2	Interrogate the Web and social media using artificial intelligence	The Web and social media present an almost inexhaustible number of ideas. Mine the Web and social media to extract “ideas” in rough form, simple if possible. Consider these to be “nuggets of ideas,” a semi-structured reservoir of raw material.
3	Put the Web output aside, and concentrate on the topic, by formulating four questions	The objective is to find four aspects of the topic that can be put as questions which together, and in sequence, <i>tell a story</i> . The topic is the description of the product, for this study of yogurt.
4	Edit the four questions, and set them up to be answered	The questions require the user to “think” about the story of what the product is. The questions will never be shown to the respondent. The questions will be used simply to promote creative thought.
5	Answer each question with four answers	Return now to the information extracted by artificial intelligence. With the four questions as a guide, and with the semi-structured reservoir of raw material, provide four answers or phrases for each question. One’s mind, one’s creative intuitions from the semi-structured reservoir of ideas, and one’s ability to craft a sentence allow one to generate the necessary four answers to each of four questions, or sixteen answers in total.
6	Create an introduction for the respondents to read	Make the introduction simple, with little information other than what the study is about, and what the respondent should do. The information will come from the answers to the questions (the messages, the elements).
7	Create a rating scale	The scale comprises a question and an anchored scale (lowest and highest scale points each have a defining phrase). What do you want the respondent to consider when making a judgment? The easiest is an evaluative attribute, such as: <i>How interested are you in this product?</i>
8	Select respondents	The entire objective of the exercise is to have respondents judge these ideas. The respondents who participate may come from the corporation’s customers, or from a commercial panel. It is always easier to work with panelists who are compensated for their participation. The fastest, easiest, and often the most productive way is to work with a commercial company.
9	Get classification information	Find out age, and gender. Put in a third classification question dealing with the topic. The APP used here is limited to three classification questions to make the system quick and inexpensive to execute.
10	Present the respondent with 24 vignettes, one after another	Each respondent evaluates a UNIQUE SET OF 24 VIGNETTES. This unique set is important. It means that increasing the number of respondents allows the researcher to test more of the “space of the combinations” rather than simply testing the same combinations again and again.
11	Collect the rating from each vignette and measure response time	The response time is the time from the presentation of the vignette on the screen to the response. The time is measured in seconds.
12	Ask the respondent another question, open-ended, about a relevant aspect of the topic	Optional, to obtain more information from the respondent about her or his feelings.
13	Transform the 9-point ratings to binary	For the typical, most-used, 9-point scale, convert the rating of 1–6 to 0. Convert the rating of 7–9 to 100. Then add a very small random number to the now-converted value of 0 or 100, respectively. The reason for the transformation is that although the rating scale is easy to use, it is not clear what a scale value means. It is a lot easier to use a binary scale. The key is how to bisect the 9-point rating scale. We are somewhat stringent, with “no” corresponding to the bottom 2/3 of the scale, and “yes” corresponding to the top 1/3 of the scale.

Step	Activity	Rationale
14	At the level of the individual respondent, use OLS (ordinary least-squares) regression to relate the presence/absence of the 16 answers to the binary ratings (0/100)	The vignettes were constructed according to a basic experimental design. The design was permuted for each respondent. The experimental design allows us to estimate the coefficients of the model for each respondent. The equation created is of the form: $\text{Binary Rating} = k_0 + k_1(A1) + k_2(A2) \dots k_{16}(D4)$. For other, bigger designs, also created in this fashion, using a permuted individual-level design, there may be more questions and more answers per question. The mathematics is precisely the same. The only difference is the number of coefficients. There is one coefficient for each answer.
15	OLS relates the presence/absence of the 16 answers to the response time	Using the same mathematics, create another model for each respondent, this time using response time as the dependent variable. Prepare the data by recoding any response time of 30 seconds or over as 30 seconds because the longer time probably represents an interruption in the experiment. The equation does not have the additive constant, k_0 . We write it as follows: $\text{Time (seconds)} = k_1(A1) + k_2(A2) \dots k_{16}(D4)$.
16	The unit of analysis is the individual coefficient	By applying OLS regression to the data from each respondent, we ensure that each respondent generates an individual set of 16 coefficients, and for interest, an additive constant as well. We use that coefficient as the basis of understanding the pattern of responses for each participant, as well as averaging the coefficient across subgroups to understand the average of the subgroup, and thus the pattern of their thinking about the topic.
17	The coefficients tell us about how the respondents react to individual elements	We can combine the additive constant with up to four answers or elements and add their values to estimate the performance of the combination. Recall from above (#16) that the additive model is written as: $\text{Binary Rating} = k_0 + k_1(A1) + k_2(A2) \dots k_{16}(D4)$. The additive constant, k_0 , tells us the likely rating on the scale of 0–100 that would be achieved if the vignette had no elements, no answers. The coefficient tells us the contribution of each element or answer. Each of the 16 answers has an average coefficient. Positive coefficients mean that adding the answer to a combination or vignette increases the proportion of respondents who rate the concept 7–9. A negative coefficient means that adding the answer to a combination or a concept decreases the proportion of respondents who rate the concepts 7–9. It is not that they do not like the idea. It is just that the element is not a particularly strong positive. We consider results from base sizes as few as 8–10 respondents. Below that base for a subgroup, the average coefficient is not stable.
18	Combine groups of respondents based on any criteria	To find subgroups, we simply combine the coefficients from the people who fall into the group. This could be gender, age, pattern of usage, etc. Then, across the respondents selected for the subgroup, average their respective additive constants, and corresponding coefficients, to estimate group performance. Alternatively, we can simply put raw data together for all the relevant respondents in a subgroup, and run one OLS regression. This is called the Grand Model. The parameters of the Grand Model typically correlate highly with the corresponding average parameters estimated by averaging the individual models.
19	Previous studies suggest norms	When the coefficient is ... here is how to interpret +15 or higher major positive +10 to +15 strong positive +5 to +10 positive 0 to +5 does not hurt, but not important 0 to –5 negative, only slightly damaging –5 to –10 negative, could be damaging –10 or lower strong negative

Step	Activity	Rationale
20	Within any topic, Mind Genomics allows us to uncover basic groups of responses, so-called Mind-Sets	These might be considered the basic mental alleles of judgment of a topic. They are not exhaustive, but suggest groups with different thoughts about what is important and relevant (positive or negative) versus irrelevant.
21	Use conventional statistics (clustering) to uncover Mind-Sets, but judgment to name them	To find Mind-Sets, we array the coefficients from our respondents (but not the additive constant), creating a matrix. The columns are the elements (our 16 elements). The rows are the respondents (our 50 respondents). We compute a measure of distance between each pair of respondents, using an accepted distance measure. In our case, we use the value (1-Pearson R). The Pearson R, or correlation varies from a high of +1 (perfect linear relation, meaning a distance of 0 between the two respondents), down to a low of -1 (perfect inverse relation, meaning a distance of 2 between the two respondents). Clustering then reveals non-overlapping groups of meaningfully different respondents, showing different Mind-Sets. We choose the fewest number of clusters or Mind-Sets (parsimony), such that these Mind-Sets tell a meaningful story (interpretability).
22	Create a set of questions from the experiment, the pattern of answers to which assigns a new person to one of the Mind-Sets uncovered in the experiment	The set of answers in the study (the original set of 16) now are filtered to identify which answers most efficiently differentiate among Mind-Sets. The PVI, personal viewpoint identifier, emerging from the experiment typically comprises 3-7 such answers from the original 16, now recast as statements. The different answers (aforementioned 3-7) are presented in random order for each person to be mind-typed and assigned to one of the Mind-Sets. The person to be assigned either agrees with the statement or disagrees with the statement (or feels the statement is important or unimportant). Thus, the response is binary, no/yes, unimportant/important, disagree/agree. The pattern of responses assigns the person to one of the Mind-Sets, the "best guess" assignment.

Table 1.
The paradigm explicated using yogurt.

that required a total of 6 hours, done at a very low cost, dealing with yogurt. The emphasis on speed, cost, and simplicity is important for the tenor of the chapter. Our goal is to present a new paradigm, more powerful than other previous approaches, as well as far faster, and significantly more economical, all leitmotifs for today, as of this writing (December, 2018). The strategy is very simple, encapsulated in **Table 1**.

5. Toward a new paradigm: front to back Mind Genomics experiment with a dairy product, yogurt

A good way to understand the features of the paradigm and what it delivers to the user comes through the demonstration with a common product that can be moderately modified, with that innovation driven by the consumer requirements. This is the typical situation, wherein there is no major technical innovation, but there is the corporate need to offer something new and attractive. The ingoing assumption is that the "new product" is somewhere "out in the ether." The features of the new product must be discovered, and not slogans, but real ideas. The effort may be too slow or cumbersome when fighting against other internal priorities,

or when the assignment must be to an outside, not-necessarily quickly responsive organization. Nor, in fact, is there the desire to wait until some start-up corporation develops a product, and then “snatch up” the corporation, making up by acquisition what one lacks in creation and innovation.

Our case history here is yogurt, although the precise steps can be used for virtually any dairy product, any food product, and indeed any product or service about which people write and talk. The specifics for yogurt are thus meant only as didactic examples.

The specific study on which we elaborate began on December 19, 2018, and finished on December 23, 2018. Of that time, the first 2 days were devoted to refining an existing software which scoured the Internet, discovering and reporting on trends, with these trends specified to be in the food industry. On December 23, we ran the study, and emerged with the results. After the holiday period, on January 4, 2019, we developed the PVI, the personal viewpoint identifier. Altogether, the paradigm, from knowledge development to testing to the personal viewpoint identifier can be said to have required approximately 48 hours of real time, taking into account the development time, as well as the disrupting time respectively. The objective is to show how to “do it” by actually doing it. In the elaboration, we present the different steps following the outline in **Table 1**.

6. The raw material

Figure 2 shows an example of the summary information for “Yogurt” yielded by the artificial intelligence system created by authors Choudhuri and Upreti and named “SamanthaSM” for this early stage. **Figures 3** and **4** show examples of the output of Samantha, using the artificial intelligence system.

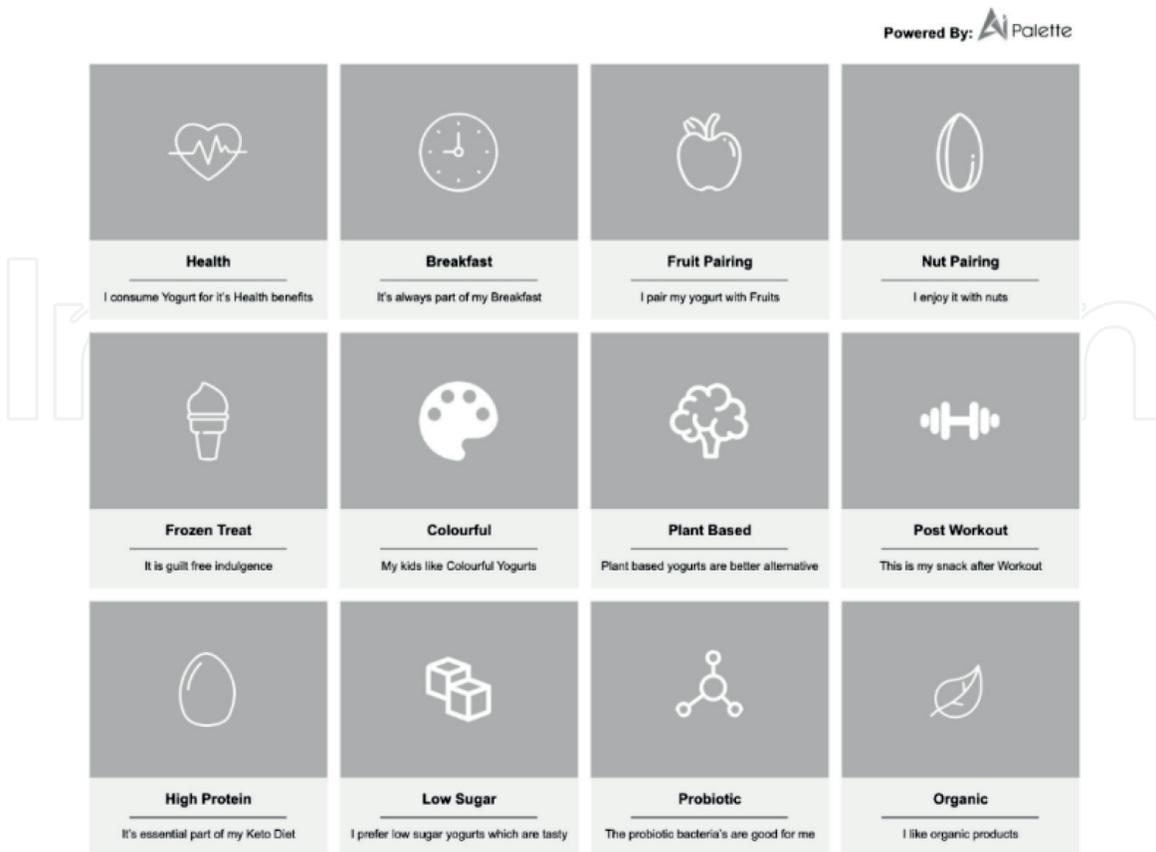


Figure 2. The matrix of information about the products. The matrix emerges from the artificial intelligence platform, “SamanthaSM,” previously designed to deal with the entire vertical of food and beverage.

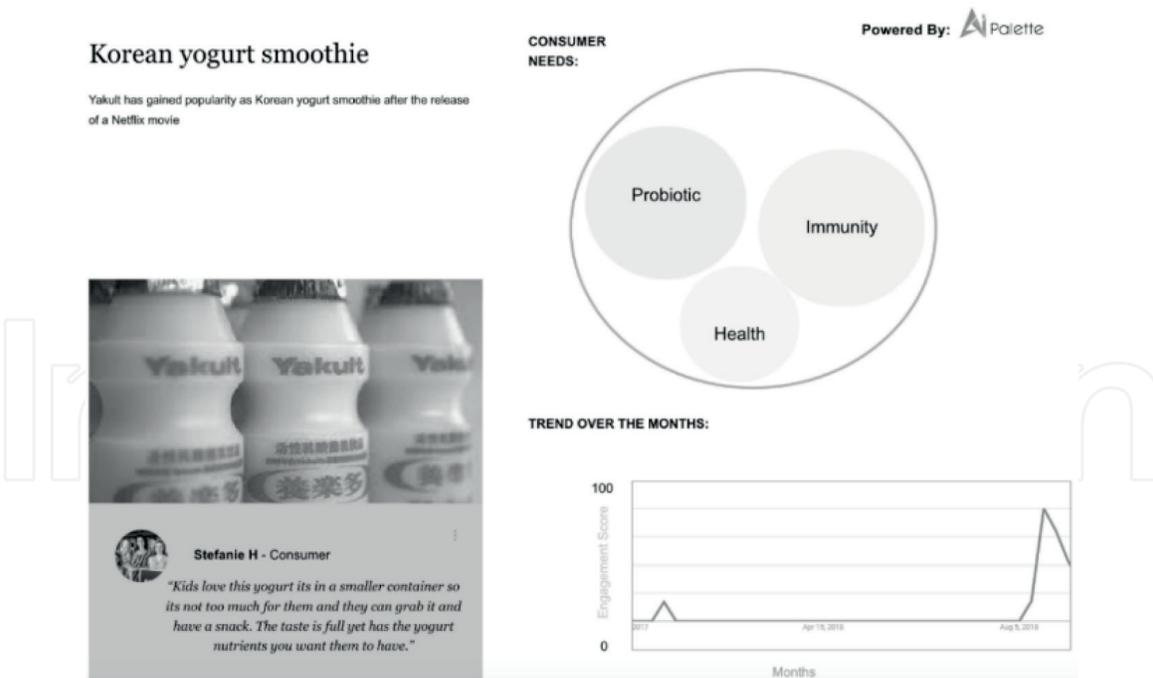


Figure 3.
 Korean smoothie deconstructed by SamanthaSM.



Figure 4.
 A health-oriented yogurt deconstructed by SamanthaSM.

Figure 2, shows a matrix of information about the products. This matrix, with circles and a short phrase, gives a sense of the different ideas. It is important to note that the effort from artificial intelligence is not to create the final questions and answers, but rather to provide hints, suggestions, from which the questions and answers are crafted. We will see the nature of the crafting later.

7. Moving from raw material to questions and answers

Mind Genomics works by presenting the respondents with combinations of ideas, messages, or in our case, combinations of answers to four questions created from the raw material shown in part in Figures 1–3. As we noted earlier, the role of artificial

Question A—What type of product is this?	
A1	A frozen yogurt
A2	A Greek yogurt
A3	A yogurt smoothie
A4	A plain yogurt
Question B—What does this product deliver in terms of sensates?	
B1	Flavorful fruit enhances the yogurt
B2	The yogurt has a colorful, picturesque appearance
B3	The texture of the yogurt is creamy and delicate
B4	The rich taste compliments the appetizing aroma
Question C—When would you eat this yogurt?	
C1	For those on the move and in need of a quick breakfast
C2	Complements a meal as the perfect side
C3	Perfect as a natural energy boost
C4	Improves recovery after daily exercise
Question D—What are the health benefits of this yogurt?	
D1	Provides your body with the protein it craves
D2	Low sugar... without sacrificing great taste
D3	Probiotic-rich and immune system boosting
D4	Only the most natural and organic ingredients

Table 2.

The four questions and four answers from each question, created by inspecting the information provided by the artificial intelligence platform, and generating the relevant statements to be used in the actual field execution.

intelligence, and particularly the SamanthaSM platform, is to present suggestions that the researcher can use to elaborate. The output from the artificial intelligence system comprises both a set of words in **Figure 2** to “jog the mind,” as well as links to deeper information (**Figures 3** and **4**). Thus, the Mind Genomics system gives room for suggested topics, as well as for the human elaboration of those topics.

Table 2 presents the set of four questions, extracted from the information provided by the artificial intelligence platform, and then elaborated and edited to move from information to questions. Each question, in turn, generates four answers, or more correctly, the researcher provides four answers to each question. The answers may be taken directly from the information provided by the artificial intelligence platform, or the answers may be polished and edited information, or perhaps even new ideas sparked by the information provided, by not actually part of the information provided. The reality is that it does not really matter where the information comes from. The Mind Genomics effort is attempting to discover “what works.” The information provided to it is the raw material. The goal is to get the best information and identify “what works.”

8. Knowledge from responses to mixtures of answers—the contribution of experimental design

One could take the 16 answers in **Table 2** and rate each of the ideas on a scale of interest. Presenting the answers one at a time and obtaining an answer is the survey

method, widely used, but unable to spark the creation of a new product idea in the way it is structured. By presenting the answers one at a time, and then requiring the respondent to rate each idea alone, we are left with ratings of single ideas, but no idea of how ideas interact with and compete with each other, as they drive interest. The respondent may also change the criterion of judgment, judging healthful ingredients more leniently, and the more indulgent features more stringently.

A potentially more productive way mixes and matches the answers, creating vignettes. The answers become the building blocks. Rather than building one answer at a time, starting with the most popular, we create combinations of answers using a recipe book (experimental design). The responses to the mixtures of answers help us understand the performance of the single elements. We do that by deconstructing the response to a blend, our mixture of answers, to the part-worth contribution of each answer. This notion was developed extensively by Norman Anderson [12], formalized as the method of conjoint measurement [13], popularized in business and academic circles by Professor Paul Green of The Wharton School of Business of the University of Pennsylvania [14, 15], and finally expanded, and made available worldwide as a method of knowledge building by author HRM [7].

9. The 4 × 4 design used in mind genomics

Mind Genomics works with various experimental designs. For these studies, we work with the so-called 4 × 4 design, namely four questions, each question requiring four answers. **Table 2** showed the raw materials, the answers or features (elements, ideas, messages) for this study. The experimental design for the 4 × 4 design comprises 24 different combinations. Each of the 16 answers or elements is statistically independent of every other answer, allowing us to analyze the data by the method of OLS (ordinary least-square regression), discussed later.

Table 3 shows the first six vignettes or test combinations for one respondent, along with the 9-point rating, the transformed value for the rating, and the response time for that vignette (test combination). Each respondent evaluates a totally different set of vignettes. The underlying experimental design is the same in a mathematical sense, but the actual vignettes differ, because a permutation scheme systematically varies the pairs of elements which appear together.

10. The study setup by the researcher and the respondent experience

At its basic level, the Mind Genomics study is an experiment, albeit couched in the form of a survey. The researcher systematically varies the stimulus inputs, the answers, according to the experiment design (**Table 3**), records the respondent's rating as well as time of response, and then analyzes the results. **Figure 5** shows what the respondent sees (test vignette) when using a smartphone. The same vignette can be presented in a slightly different configuration to fit the screen of a personal computer or a tablet.

The typical Mind Genomics experiment with BimiLeap® takes approximately 4–5 minutes from start to finish. Many respondents begin with the typical strategy of trying to be “correct.” The respondent may spend more time at the start than at the end, reading the vignettes, in order to make sure that they have gotten all the relevant information. By the time the respondent reaches second, and certainly the third vignette, however, this effort begins to subside, and the respondent answers, almost automatically, at an intuitive level, the System 1 of Nobel Laureate Daniel Kahneman [16].

Order	1	2	3	4	5	6
A1	0	0	0	1	0	1
A2	0	0	0	0	0	0
A3	0	0	1	0	1	0
A4	0	0	0	0	0	0
B1	0	0	0	0	1	1
B2	0	0	0	0	0	0
B3	1	1	0	0	0	0
B4	0	0	1	1	0	0
C1	1	0	1	0	1	0
C2	0	1	0	1	0	0
C3	0	0	0	0	0	0
C4	0	0	0	0	0	1
D1	1	0	0	0	0	0
D2	0	0	0	1	1	0
D3	0	0	1	0	0	0
D4	0	1	0	0	0	1
Rating	7	7	8	8	8	5
Binary	101	100	100	101	101	0
Res Time	13	10	6	5	5	3

Table 3. The first six vignettes for one respondent. The 4 × 4 design prescribes 24 vignettes of precise design in terms of the elements which each vignette comprises.

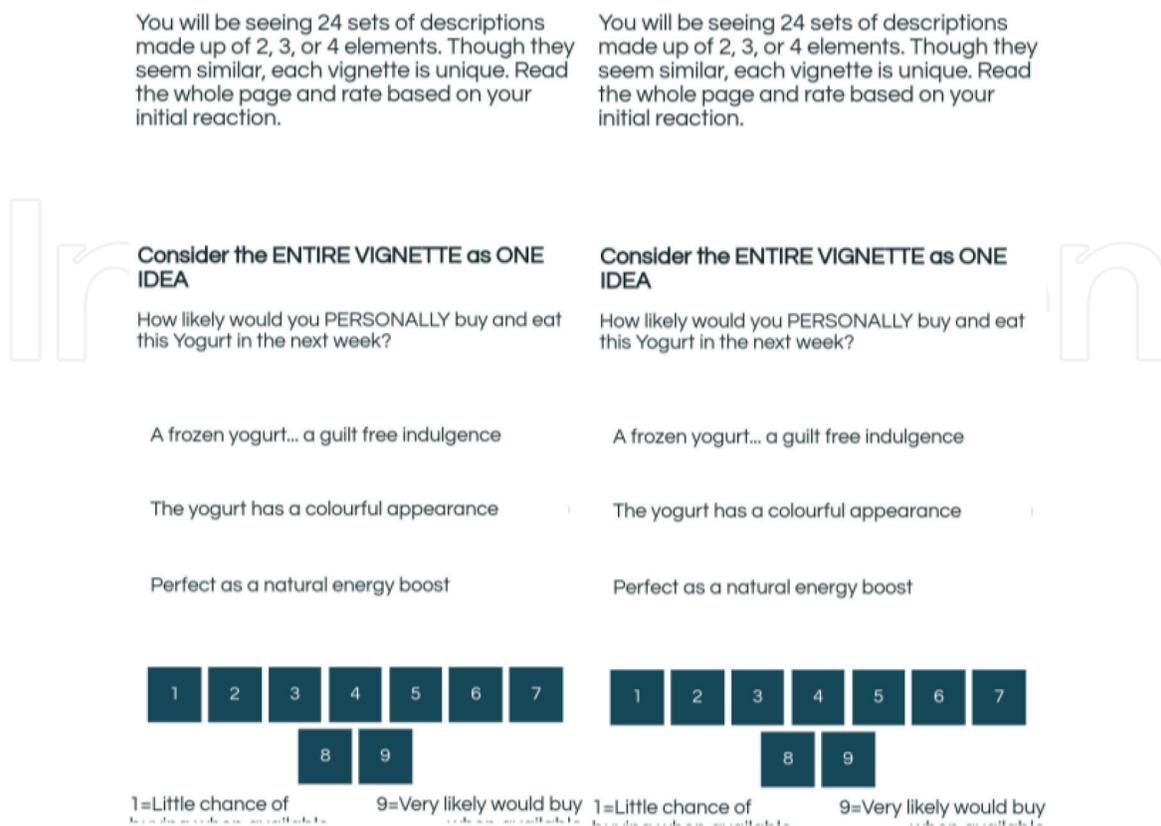


Figure 5. The respondent experience when using a smartphone with a small screen.

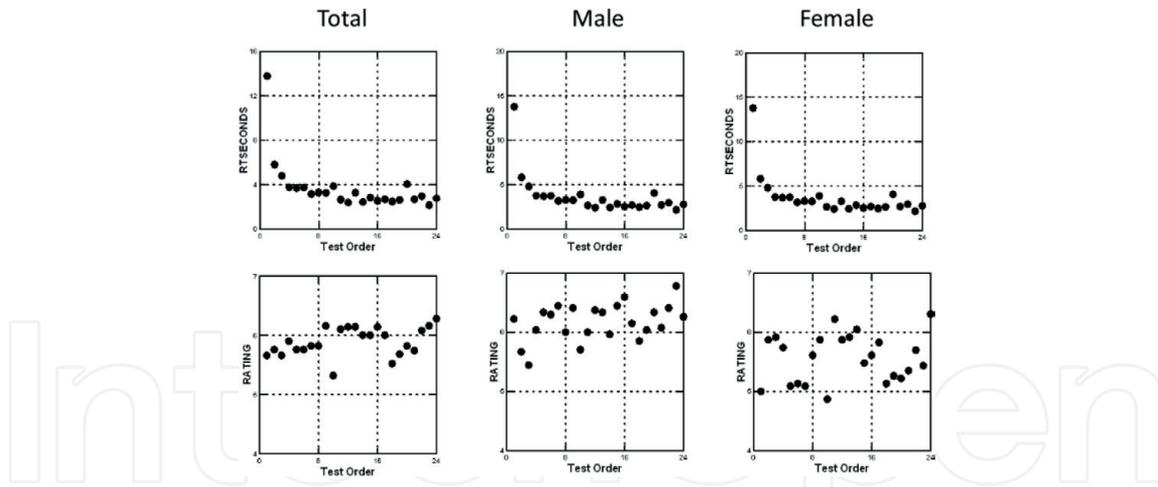


Figure 6. The average time in seconds needed for a respondent to read a vignette and assign a rating (top row of graphs), and the average rating assigned to the test vignette (bottom row of graphs.).

Figure 6 shows the external dynamics of the experiment. The top set of figures shows the average response time in seconds, by position of the vignette. We see that whether we deal with the Total Panel, with males, or with females, the pattern is virtually the same. The average response time after the first vignette tested drops to a constant level. Despite the long time and the extensive number of vignettes, respondents still seem to vary their ratings.

11. What drives interest in yogurt: results from our study

Up to now, we have focused on the setup and execution of the study. The more interesting part of the study comes from the discovery of just how the answers, the stimulus inputs under the researcher's control, "drive" the response, in this case interest. In this section, we look at the results from our experiment with 50 respondents. We will look at the additive constant to get a sense of baseline interest, then at the coefficients to see which elements or answers drive interest, and then search for Mind-Sets, groups of ideas which "move together." Each of our 50 respondents will be assigned to a Mind-Set based upon the pattern of coefficients. **Table 4** shows the results.

- a. Total Panel shows an additive constant of 56, meaning that in the absence of any elements in the vignette, we expect 56% of the answers to be ratings of 7–9. Basically, yogurt is liked. It will be up to the elements to drive liking much higher.
- b. The "Total Panel," with all 50 respondents, shows NO very strong elements. This means that if we continue to try these types of ideas, it is likely that for the general population nothing will work, or when some element works, it will be probably by accident.
- c. The answer is dividing the respondents into Mind-Sets. The Mind-Sets are selected from the mathematical clustering to "make sense." The computer only divides the respondents by the pattern of coefficients. It is the researcher and the marketer who must make sense of the Mind-Sets.
- d. Mind-Set MS1: Modestly interested in yogurt (additive constant 37), but interested in the type of yogurt, especially high protein and convenient. They may like yogurt for its probiotic qualities. We could call these the health-through-a good-tasting-food.

- e. Mind-Set MS2: A yogurt aficionado (higher additive constant of 58), likes the multisensory appeal of yogurt.
- f. Mind-Set MS3: A yogurt aficionado (higher additive constant of 48), but probably looking for a low-calorie snack.

The prudent developer might well repeat this step 3–4 times, with different sampling of ideas from SamanthaSM, and with new populations of respondents, perhaps retaining the strong performing ideas, for a final test (e.g., step #5) comprising only strong performing answers or elements which have proved themselves.

Group	TOT	MS1	MS2	MS3	
Tentative name		Health & good taste	Multisensory	Low-calorie snack	
Base size	50	22	13	15	
Additive constant	56	37	58	58	
Question A: Type					
A1	A frozen yogurt... a guilt-free indulgence	-3	9	8	-30
A2	A Greek yogurt... high in protein	-3	14	4	-34
A3	A yogurt smoothie... no spoon required	-4	17	-1	-37
A4	A plain yogurt... versatile, customizable	-7	8	1	-37
Question B: Traits					
B1	Flavorful fruit enhances the yogurt... taste and health	4	-3	25	-4
B2	The yogurt has a colorful appearance	1	-5	22	-8
B3	Nutrient-rich nuts improve the texture and flavor-profile of the yogurt	1	-3	11	-3
B4	The yogurt is plant-based... a better alternative	-2	-6	22	-16
Question C: Situation					
C3	Perfect as a natural energy boost	0	5	-3	-5
C2	A healthy meal and snack alternative	-1	-2	-6	4
C4	Improves recovery after daily exercise	-1	2	-9	1
C1	For those in need of a quick breakfast	-6	-8	-12	0
Question D: Benefit					
D3	Probiotic-rich... immune system boosting	2	15	-14	-3
D2	Low sugar... without sacrificing great taste	0	9	-28	10
D4	Only the most natural and organic ingredients	-1	9	-15	-5
D1	Provides your body with the protein it craves... essential for keto diets	-4	8	-21	-6

Table 4. The results from the study, showing the coefficients for interest (binary transform) both from the Total Panel (ToT), and from the three complementary Mind-Sets (MS1, MS2, MS3).

12. Response times and their relation to Mind-Sets

We now turn to the second important variable, response time. The BimiLeap® APP from Mind Genomics measured the number of seconds from the presentation of the vignette on the screen to the response. The analysis deconstructs the response time in seconds into the part-worth contribution of each element in the vignette. The model does not have an additive constant, so that the response time is “0” in the absence of any elements. Furthermore, **Figure 6** (top panels) suggests that the response time to the first vignette should be discarded. That response time is longer than the other response times, probably because when making that first rating, the respondent is not accustomed to the procedure, and there may be some issues both with eye-hand coordination, and with using the scale. By the second vignette, however, the response time is quite stable.

Response times from vignettes 2–24		TOT	MS1	MS2	MS3
			Health and good taste	Multisensory	Low-calorie snack
Question A: Type					
A2	A Greek yogurt... high in protein	0.7	1.1	0.9	0.1
A3	A yogurt smoothie... no spoon required	1.0	1.1	0.9	0.9
A4	A plain yogurt... versatile, customizable	1.0	1.2	0.8	1.0
A1	A frozen yogurt... a guilt-free indulgence	1.0	1.3	0.8	0.9
Question B: Traits					
B1	Flavorful fruit enhances the yogurt... taste and health	0.9	1.0	0.9	0.7
B3	Nutrient-rich nuts improve the texture and flavor-profile of the yogurt	1.0	1.5	0.5	0.7
B4	The yogurt is plant-based... a better alternative	1.0	1.8	0.2	0.6
B2	The yogurt has a colorful appearance	1.2	1.8	0.1	1.0
Question C: Situation					
C2	A healthy meal and snack alternative	0.8	0.4	0.7	1.5
C4	Improves recovery after daily exercise	1.0	0.5	1.3	1.5
C3	Perfect as a natural energy boost	1.1	0.7	1.6	1.0
C1	For those in need of a quick breakfast	1.2	0.9	1.6	1.5
Question D: Benefit					
D3	Probiotic-rich... immune system boosting	0.3	-0.2	-0.3	1.4
D1	Provides your body with the protein it craves... essential for keto diets	0.5	0.1	0.4	1.4
D2	Low sugar... without sacrificing great taste	0.7	0.9	0.5	0.7
D4	Only the most natural and organic ingredients	1.3	1.4	0.7	1.6

Table 5. Coefficients for response time both from the Total Panel (TOT), and from the three complementary Mind-Sets (MS1, MS2, MS3) emerging from the rating question.

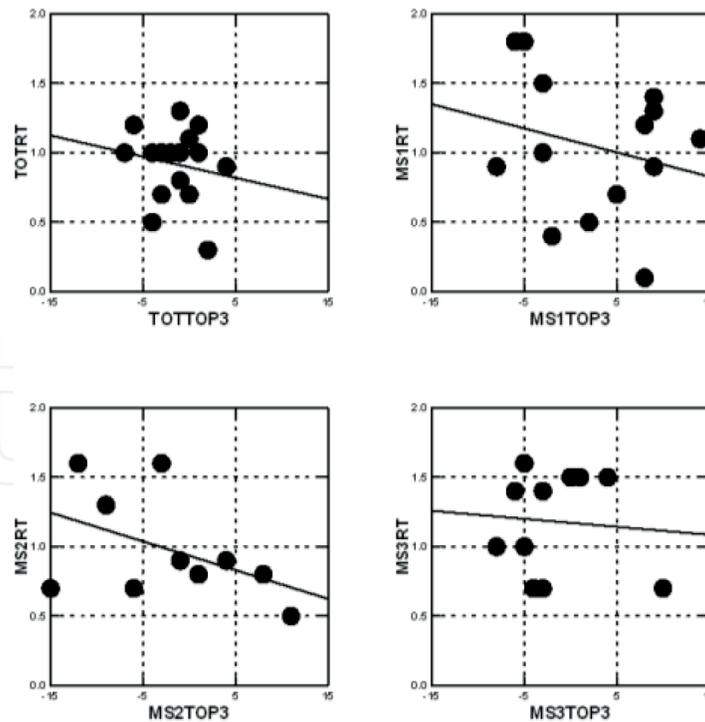


Figure 7. Scatterplot showing the relation between the coefficient for response time (ordinate) and the coefficient for interest (abscissa). The patterns are shown for the Total Panel, and for the three Mind-Sets, respectively.

Our objective here is to discover whether the 16 answers each generate the same response time. The way to do that is again by OLS regression. This time, however, we put all the relevant data into one set, and estimate one “grand” regression model for that relevant data. By “relevant,” we mean first eliminating ALL data from the first vignette (order #1), no matter who the respondent happens to be. We then either divide the data into three groups, depending upon the Mind-Set of the respondent, allowing us to estimate the response time per element for each Mind-Set, or we look at all the data in one group for Total Panel. We run the Grand Models for this analysis, rather than running the individual-level models.

Table 5 shows the coefficients for response time estimated for each of the 16 elements, both for the Total Panel and, respectively, for the three Mind-Sets generated from the ratings assigned to the vignettes. **Table 5** shows clear differences in estimated response time (RT) across the elements, and across the Mind-Sets.

When we plot response time against interest, with the points corresponding to the 16 coefficients for the 16 elements, **Figure 7** suggests differences in response time may not strongly co-vary with the interest in the message estimated from the rating. That is, more interesting messages or elements are not necessarily responded to more quickly. *This lack of strong co-variation between interest and response time differs from what has been recently uncovered by author HRM in a study of the same type, dealing with a political issue, the Russian-Ukrainian conflict of 2018, rather than yogurt.* It may well be that the studies of RT require topics which are involving. Yogurt simply may be not particularly involving even though the data may make sense.

13. Finding these respondents in the population

Our efforts to create a new yogurt concept through experimental design (BimiLeap®), powered by access to trends through artificial intelligence (SamanthaSM) have uncovered a new way to understand a product category and prepare to create new concepts. We see clearly from the data in **Table 4** as well

as from the array of previous studies on dairy that people perceive the features of a dairy product in different ways, at least in terms of what they consider to be interesting and important. Our identification of the mental genomes, these alleles of preference, pertains only to the respondents whom we tested, generally small groups of consumers from easy, affordable panels. How do we generalize our findings, either to discovering the distribution of these basic Mind-Sets in the population or, more importantly, discovering individuals who are members of these Mind-Sets, and who can be further studied? The further studies may be as simple as their preferences for concepts created for the product (e.g., yogurt products), on to purchase and consumption patterns, and even beyond to possible health and genetic correlates of segment membership? One approach to predicting Mind-Set membership looks at the pattern of coefficients for the Mind-Sets (**Table 4**), and selects elements showing the greatest differentiating power, that is, the biggest difference for the average panelist. Each selected element is then edited to become a question, to be answered NO or YES, or some other appropriate pair of responses for the same type of binary decision. The questions are incorporated into a short questionnaire. The pattern of responses shows the Mind-Set to which the respondent probably belongs. The feedback to the respondent or to a marketing company using the data appears in **Figure 6**, in the three right panels. The personal viewpoint identifier is easy to create using summary data, is quick to administer, and can be configured as either a “fun” tool to engage customers, or as a more serious tool to understand the mind of the consumer. From one study, one can proceed to type up to the millions of respondents, should one wish to study entire populations. For this study on yogurt, the personal viewpoint identifier is shown in demonstration form in this link: <http://162.243.165.37:3838/TT04>.

14. Five-year prospects: trend definition, product design, mass mind-typing, personalization

As presented here, the approach we present begins with a combination of social data analysis and experimental science, moving on to new vistas. These vistas include a new way of exploring ideas, uncovering possibly new-to-the-world mind-genomes, and finally, understanding how neurophysiological processes indicated by response time co-vary with interest in the product. We now move beyond the data to suggest opportunities and applications, some of which are already in their nascent stages, and some of which are easily done, but simply have not been implemented.

Trend definition: The objective of trend spotting is to identify general patterns of what is happening, usually from an exploration of websites and conversations, and their distillation into general patterns. The patterns provide broad patterns, not specifics. Thus, for dairy, we might find a trend emerging for cultured milk products like kefir, combined with new flavors and interesting incorporations, such as chia seeds. The trend spotter may guess about the nature of this trend. What would happen if the new ideas could be incorporated in a Mind Genomics study, with the respondents asked to rate the likelihood of each vignette as an emerging trend? The answers would range from absolutely never to current to approximately a year or a two in the future. In this case, the trend is defined not so much by what one observes as by a combination of that which is observed, with some conscious elaborations of what might be.

Product design: This chapter presents the Mind Genomics as an effort to deconstruct the response to individual features of dairy products based upon the response to vignettes. One can also look at the Mind Genomics as a “Mixmaster” of ideas,

whether these ideas or elements be based upon yogurt, upon dairy in general, or even other foods and situations. When these elements from disparate sources are combined, elements not only for yogurt, for example, the outcome is a new set of possible products. The promising ideas can be combined. When, for the most part, the ideas from different areas really do not work together, the ratings for the combinations will be low, and there will not be any strong performing elements, suggesting that the raw materials simply do not work together.

Perhaps the most important contribution of Mind Genomics is to combine profound knowledge of a person's interest in dairy products with both the ability to guide the person to eat better, and to understand how preferences for dairy co-vary with behavior. The full elaboration of the social use of Mind Genomics for health issues and dairy awaits the new generation of researchers, interest in dairy, in health, and in commerce, respectively. We have presented early indications and of these new developments.

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Author details

Ryan Zemel¹, Somsubhra Gan Choudhuri², Attila Gere³, Himanshu Upreti², Yehoshua Deite⁴, Petra Papajorgji⁵ and Howard Moskowitz^{6*}

1 Limbic Reviews, Chicago, IL USA

2 AI Palette, Inc., Singapore, Republic of Singapore

3 Faculty of Food Science, Department of Postharvest Science and Sensory Evaluation, Szent István University, Budapest, Hungary

4 Sifra Digital Inc., Jerusalem, Israel

5 Universiteti European i Tiranes, Tirane, Albania

6 Mind Genomics Associates, Inc., White Plains, NY, USA

*Address all correspondence to: mjihrm@gmail.com

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References

- [1] Govindarajan V, Trimble C. Strategic innovation and the science of learning. MIT Sloan Management Review. 2004;**45**:67
- [2] van Kleef E, van Trijp HCM, Luning P. Consumer research in the early stages of new product development: A critical review of methods and techniques. Food Quality and Preference 2005;**16**(3): 181-201. Available from: <http://www.sciencedirect.com/science/article/pii/S0950329304000886>
- [3] Esmerino EA, Ferraz JP, Filho ERT, Pinto LPF, Freitas MQ, Cruz AG, et al. Consumers' perceptions toward 3 different fermented dairy products: Insights from focus groups, word association, and projective mapping. Journal of Dairy Science. 2017;**100**(11):8849-8860. Available from: <http://www.sciencedirect.com/science/article/pii/S0022030217308159>
- [4] Lusk JL. Consumer research with Big Data: Applications from the Food Demand Survey (FoodS). American Journal of Agricultural Economics. 2017;**99**(2): 303-320. DOI: 10.1093/ajae/aaw110
- [5] Artz M. NPS—The one measure you really need to grow? Controlling and Management Review. 2017;**61**(1):32-38. DOI: 10.1007/s12176-017-0002-x
- [6] Moskowitz HR, Gofman A, Beckley J, Ashman H. Founding a new science: Mind genomics. Journal of Sensory Studies. 2006;**21**(3):266-307. DOI: 10.1111/j.1745-459X.2004.00066.x
- [7] Moskowitz H, Gofman A. Selling Blue Elephants: How to Make Great Products That People Want Before They Even Know They Want Them. First. Philadelphia, Pennsylvania: Wharton School Publishing; 2007
- [8] Moskowitz HR. Mind genomics® and texture. In: Food Texture Design and Optimization. John Wiley & Sons, Ltd; 2014. pp. 342-377. Available from: <https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118765616.ch14>
- [9] Waclawski E. How I use it: Survey monkey. Occupational Medicine. 2012; **62**(6):477. DOI: 10.1093/occmed/kqs075
- [10] Box GEP, Hunter JS, Hunter WG. Statistics for Experimenters: Design, Innovation, and Discovery. 2nd ed. Hoboken, NJ: Wiley-Interscience; 2005
- [11] Moskowitz HR, Gofman A, Itty B, Katz R, Manchaiah M, Ma Z. Rapid, inexpensive, actionable concept generation and optimization: The use and promise of self-authoring conjoint analysis for the food service industry. Food Service Technology. 2001;**1**(3):149-167
- [12] Anderson NH. Foundations of Information Integration Theory. Cambridge, Massachusetts: Academic Press; 1981
- [13] Luce RD, Tukey JW. Simultaneous conjoint measurement: A new type of fundamental measurement. The Journal of Mathematical Psychology. 1964;**1**(1):1-27. Available from: <http://www.sciencedirect.com/science/article/pii/002224966490015X>
- [14] Green PE, Rao VR. Conjoint measurement for quantifying judgmental data. Journal of Marketing Research. 1971;**8**(3):355-363. Available from: <http://www.jstor.org/stable/3149575>
- [15] Green PE, Srinivasan V. Conjoint analysis in marketing: New developments with implications for research and practice. Journal of Marketing. 1990;**54**(4):3-19. Available from: <http://www.jstor.org/stable/1251756>
- [16] Kahneman D. Thinking, Fast and Slow. New York, NY, USA: Farrar, Straus and Giroux; 2011. Available from: <https://books.google.hu/books?id=ZuKTvERuPG8C>