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INTERNATIONAL JOURNAL ON FOOD SYSTEM DYNAMICS

Int. J. Food System Dynamics 14 (4), 2023, 367-380

DOI: https://dx.doi.org/10.18461/ijfsd.v14i4.H1

Sourcing and Vetting Ideas for Sustainability in the Retail Supply Chain: The Contribution of Artificial Intelligence Coupled with Mind Genomics

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Received December 2022, accepted September 2023, available online November 2023

ABSTRACT

This study analyzes the sustainability of the retail supply chain. The paper shows the integration of Artificial Intelligence (AI) with Mind Genomics to understand how ordinary people think about food sustainability. The combination reveals how people think about the topic, from the point of view of what information regarding sustainability in retail is attractive to the ordinary person, what information is believable, and finally, the nature of different ways of thinking about sustainability in retail, namely mindsets. The paper closes with the PVI (personal viewpoint identifier) evaluation.

Keywords: *Mind genomics; artificial intelligence; sustainability; food retail supply chain.*

1 Introduction

Today's world of problems focuses on many directions. Simply knowing that there are problems does not present the knower with any but the most straightforward solutions. Furthermore, even when the issues are more deeply understood, e.g., by experts or at least by those who have studied the problems, there is no reason that an answer should be forthcoming. Finally, if an answer is forthcoming, will the solution be technically and commercially feasible, and will the answer be one that the public accepts?

The previous paragraph suggests that one of today's opportunities is identifying how the public will think about a solution. Even when the solution is technically complex, with the actual solution challenging to achieve and difficult to explain, is there a way to gauge the public's response to the possible solutions (Saulo and Moskowitz, 2011; Porretta et al., 2019)?

The standard methods for understanding how to communicate problems and solutions emerge from sociology, public opinion polling, and consumer research (Gofman, 2012; Doherty and Nelson, 2010).

Sociology is a science attempting to create a body of understanding about society, using problems as aspects to study. Sociology focuses on the nature of society and its issues, whether these are socially driven issues or the social response to other matters, such as environmental change. In contrast, public opinion polling comprises a set of methods focusing on measuring the population's response to people, situations, problems, and solutions. By its very nature, public opinion polling is reactive to the situation at hand, measuring that which exists or could be imagined easily. Finally, consumer research focuses on how people make decisions about their everyday lives, generally dealing with issues of products and services that are provided at a price (Steinman, 2009; Gofman and Moskowitz, 2010). Consumer research comprises problems or issues, behavioral responses to the problem or issue, and measurement methods (Gere, Radvanyi, and Moskowitz, 2017). It is interesting to look at these three approaches dealing with issues of the retail supply chain. In that case, the sociologist might focus on the different patterns of concerns and actions across countries or social strata. The questions would be general and attempt to discern available patterns to build the knowledge base. The public opinion pollster would be interested in the differences in people's attitudes toward the same problem, by geographic location, income, etc., compared to other issues facing people. Finally, the consumer researcher would focus more on responses to solutions, such as expected changes in buying patterns for different solutions. All three areas, sociology, public opinion polling, and consumer research, are typically limited in focus, dealing with the study of a problem rather than the combination of problem statement and creation of solutions. Furthermore, they need to be oriented to the rapid consumer-driven definition of problems and the discovery of consumer-relevant solutions. This study introduces a new approach to accomplish the three goals, designed to be quickly done by anyone, and be scalable. Moreover, the results could be stored in a knowledge base (Hesse, Moser, and Riley, 2015). This study introduces the problem from the bottom up, using technology to uncover the problem, identify solutions from the consumer's point of view, and identify solutions that may work (Todri et al., 2020; Meise et al., 2014; Mehta-Shah, Mehta, and Zemel, 2021).

2 Tool 1 – Understanding the Algebra of the Mind using Mind Genomics

During the past sixty years, psychologists and consumer researchers have made great strides in understanding how people respond to stimuli, such as messages conveying single ideas or combinations of messages conveying various ideas. It seems prosaic even to present the typical questionnaire approach used seemingly ad infinitum by companies wanting to know about their services and products. Respondents have no issue rating one or a variety of ideas on a rating scale, which are presented one at a time. This so-called questionnaire method has led to remarkable insights in many areas, ranging from evaluating simple experiences to evaluating issues of global importance.

The one-at-a-time approach, popular as it is, has many things that could be improved. The most severe flaw is that the system can be 'gamed', as the respondent facing the questionnaire tries to outguess the person who has developed the questionnaire, or the person who is administering the questionnaire, the 'interviewer.' Consequently, the researcher generally takes precautions like randomizing the questions to avoid order bias (e.g., the first question asked is often rated higher). Another approach is disguising the language or presenting the same question twice or thrice in different formats.

One-at-a-time research is not a realistic way to deeply understand compound and complex problems. The reason is that nature rarely gives us simple, isolated aspects of a topic in a deconstructed fashion, namely, in the one-at-a-time fashion. Instead, nature is inconvenient and messy, presenting us with combinations of inputs. Sometimes, these inputs are compound experiences comprising different components. The realization that this is the way nature works has led to a different way to study nature, using systematically designed mixtures of ideas. These mixtures are set up so that the ideas are presented together, not haphazardly but in a controlled fashion. The mixtures of ideas are called 'vignettes', known combinations of the ideas, the same ideas combined in different ways. To the respondent, the mixtures may seem random. At the end of the exercise, with the elements or messages put together according to the underlying plan, the so-called 'experimental design', statistical analysis (regression) deconstructs the response to reveal how the elements drive responses. This deconstruction allows the scientist to understand how the person thinks about the problem. Furthermore, the regression models emerge with coefficients, the metric of how the element drives the rating.

In a sense, these coefficients 'summarize the mind' for the topic, at least in terms of how they drive specific, interpretable elements or messages. Coefficients for different people can be organized into groups based on their patterns. The method is clustering, and the output is a deeper understanding of how a person responds to the different ideas in a topic (Moskowitz, 2012; Moskowitz, Beckley, and Ashman, 2006).

Over the past three decades, the Mind Genomics approach has been used successfully in various fields to understand how people make decisions. The applications range from consumer products and services (Moskowitz and Gofman, 2007), legal issues (Moskowitz, Wren, and Papajorgji, 2020), medical communications (Oyalowo et al., 2022), education (Losavio and Gollub, 2022; Todri et al., 2020), political sciences (Moskowitz et al., 2022) and many more.

More recent applications, especially in the world of retail, have been presented in a variety of publications dealing with Covid and how it affects the shopping experience for food (Saulo et al., 2019; Theriot et al., 2021), and tourism (Papajorgji et al., 2021). Over the past decades, since its introduction into the research community, the effort has been to create an easy DIY (do-it-yourself system). The early approaches were cumbersome because the analysis was overly involved, and even the setup by the researcher was not simple. Around 2016 and later, the process was simplified tremendously by creating a total DIY system known as BimiLeap, an abbreviation for Big Mind Learning Application (www.BimiLeap.com). The entire process, from setup to analysis and reporting, was virtually automatic. All the researchers had to do was think about the topic, construct the four questions, and then create the four answers to each question. In addition, the researcher had to create a short introduction for the respondent to define what the study was about and then create a rating question.

The previous process seemed simple, requiring the researcher to consider the topic. The approach mixed the answers from the four questions into small, easy-to-read combinations called vignettes. A vignette comprised a minimum of two and a maximum of four, at most one answer from any question.

The process was templated, as seen by the abovementioned program, www.BimiLeap.com. The underlying program would then go through the process comprising these steps:

1. An underlying structure, the experimental design (Gofman and Moskowitz, 2010) prescribed exactly twenty-four combinations. Each of the sixteen answers appeared five times.

2. By design, each vignette can be complete or incomplete. Complete means one element or one answer from each question.

3. For each respondent, the BimiLeap system presents the test stimuli, acquires the rating (usually on a short rating scale, e.g., a 5-point scale), as well as measuring the response time, defined as time between the presentation of the vignette on the computer screen and rating).

4. By convention, although not necessarily, the BimiLeap system converts the rating into a binary scale. For the data presented here, the ratings of 1-3 are converted to 0 (zero), and the ratings of 4-5 are converted to 1 (one). This first transformation is advisable because most users of the information need help figuring out what to do with Likert Scales, such as the 5-point scale. These users of the information feel more comfortable with percentages. The conversion ends up creating a percentage scale.

5. The underlying BimiLeap system 'permuted' the basic design. That is, the mathematics of the design was maintained, but the twenty-four combinations differed from one respondent to another. A good analogy is that the MRI (Magnetic Resonance Imaging) takes pictures of the same tissue from different vantage points and, through a computer program, creates a composite 3-D view of the tissue. The permutation means that each respondent ends up evaluating different combinations. The key benefits are that one does not have to know the correct answer but instead uses the data from many people to explore the ample design space. Rather than spending money to reduce the variability around an area in the 'design space' thought to be most promising, the researcher spends money to explore.

6. The other benefit is that each respondent evaluates just the right combination of vignettes to allow the estimating of an individual-level model. This individual-level modelling allows the researcher to classify the respondents by the pattern of their reactions to the relevant stimuli rather than by geo-demographic variables or by their pattern to macro-level questions.

7. The analysis of the data is purely mathematical. The data for each respondent, the original rating, and the transformed rating (as well as the response time) suffice to estimate the coefficients by OLS (ordinary least-squares) regression. The database for each respondent comprises 24 rows, one row for each of the 24 vignettes evaluated by the respondent. The independent variables for OLS are the 16 elements amounting to 16 independent variables. Each cell corresponding to a vignette and an element contains the value '1' (one) when the element was present in

the vignette or the value ‘0’ (zero) when the element was absent from the vignette. The experimental design ensured that any row corresponding to a vignette would have at least two ‘1’s (one), and at most four ‘1’s (one).

8. The basic equation relating the presence/absence of the 16 elements to the binary transformed rating (namely, 0/100 from zero to hundred) is expr *Transformed Rating = k0 + k1(A1) + k2(A2) ..+ k16(D4)*, where the independent variables A1-D4 comprise the 16 answers. The basic equation relating the presence/absence of the 16 elements to the response time (in seconds) is expressed as the same equation, except the equation lacks the additive constant: *Response Time = k1(A1) + k2(A2) .. k16(D4).*

9. Each respondent generates her or his equation for transformed rating vs. elements, for response time vs. elements. The set of individual coefficients for transformed rating can be further analyzed using clustering technologies to identify groups of respondents with similar patterns of coefficients. These are called ‘mindsets.’ The clustering method is k-means (Mucherino, Papajorgji, and Pardalos, 2009), which operates at the simple level of computing the Pearson correlation between pairs of respondents based upon their 16 coefficients for elements and assigns each respondent to a group of similar-patterned coefficients.

10. At the end of the analysis, all data from individual respondents belonging to a specific group (e.g., males or females, different mindsets) are stored in the same database, and the regression analysis is performed on the entire data set.

11. Nearly three decades of experience with Mind Genomics applied to many problems suggest that the respondent's task is straightforward. However, the task of the researcher is an entirely different thing. The respondent needs to be instructed to evaluate different vignettes and rate each. Of course, the repeated set of vignettes is a little confusing to the respondent because the continuing combination change makes it impossible for the respondent to game the system. The respondent quickly tires of being correct, simply giving her or his first or ‘gut’ opinion. The respondent often complains about the ability to know whether she or he assigned the vignette the correct rating. That confusion is not a negative but simply a recognition that the experimental design makes it impossible to guess. Respondents give their immediate opinion, an action that they think produces random data. Nothing could be further from the truth, as the results show.

3 Tool 2 – Artificial Intelligence to identify the Questions and Answers needed by Mind Genomics

As straightforward as Mind Genomics is, past experiences suggest that the typical user stumbles repeatedly, stumbling at the same step. This stumbling block is the creation of the four ideas. Individuals, even those new to Mind Genomics, have no problem when instructed to select a 'topic,' the first step. Furthermore, when the four questions have been selected, these 'newbies' to the Mind Genomics process stumble a bit but eventually become capable of providing the necessary four answers to each question.

By elimination, the remaining step, selecting four questions, emerges as the fundamental stumbling block. When Mind Genomics emerged, the cumbersome process overshadowed the difficulties of creating questions and answers. With its many steps, the analysis above ensured that only a few individuals would use Mind Genomics. The analytics were daunting, not so much in and of themselves, but the need to manually link together sophisticated analytic procedures, such as the individual-level OLS regression with the clustering. The stumbling block has re-emerged with the creation of the automatic analysis that characterizes today's Mind Genomics, instantiated in the BimiLeap system. Now, the selection of questions and, to some extent, the selection of answers to those questions is complicated. This paper is not the right venue to explore the range of difficulties experienced by the researcher trying to come up with suitable up-front material.

No matter the researcher's experience level, the demand to come up with four questions emerges as quite daunting. For the less experienced, and all too often for the novice, providing four elements that tell a story is where the effort ends, and the would-be-researcher abandons the process. Recognizing that up-front 'thinking', or more correctly 'difficulties with up-front thinking' is the main obstacle, justified the effort to find a new way to help people provide questions and answers. The range of alternative topics one could explore emerged as daunting. The issue is to supply a process that generates the questions and the answers upon demand in a practical, intriguing way and, ultimately, education. This step evolved to using artificial intelligence to create the four questions and the four answers to each question. The desire and need to make the up-front effort easier for all users is familiar and did not suddenly emerge when access to artificial intelligence became easier. A decade's worth of experience using Mind Genomics produced in its wake of user requests to create a way to fill the 4x4 matrix, four questions by four answers, referred to as the 4x4 model. The 6x6 predecessor model was even more daunting, with six questions and six answers. Until the emergence of easy access to artificial intelligence, e.g., that provided by (Openai.Com, n.d.) OpenAI, the task seemed impossible. The reality of thinking one's way through the set-up could have been more challenging and encouraging.

However, with the emergence of OpenAI – a set of models that can understand and generate natural language, the discomfort of thinking about a topic in depth began to subside.

4 Using the Combination of Artificial Intelligence and Mind Genomics to address the Research Call

The remainder of this paper demonstrates what the combination of Mind Genomics and artificial intelligence accomplished in response to the call for a paper on sustainability.

The topic is shown below. The paper shows the steps. As a matter of record, the entire integrated process took a total of approximately 70 minutes; 40 minutes to set up the study using OpenAI' sGPT-3 DaVinci model (OpenAI-GPT-3, n.d.) (in the form of Idea Coach, now part of the BimiLeap program at www.BimiLeap.com), and then 30 minutes in the 'field' with respondents, from launch to a completed, thoroughly analyzed report.

Step 1: Using www.BimiLeap.com, create a new study. Give the study a name.

Step 2: Proceed to the creation of four questions. Instead of thinking of the four questions, use the Idea Coach to invoke AI (Artificial Intelligence).

The Idea Coach asks for a short paragraph about the topic of the study. The paragraph below, explaining the study, is taken almost verbatim from the 'call for papers.'

Analytics and modeling can enhance retail supply chains' economic, environmental, and social sustainability. The objective is to accelerate the development and application of quantitative approaches for problem-solving and decision-making to develop sustainable retail operations.

Step 3: Idea Coach returns with up to 30 questions that can be asked. For this topic and the above paragraph, the first effort returned with only ten questions, shown below in Table 1. A second and third inquiry (not shown) each returned with 30 questions. This paper aims to proceed with the first output of Idea Coach to test the usefulness of artificial intelligence.

Table 1.
The questions returned by Idea Coach.

The ten questions returned by Idea Coach, based on the problem statement
1. How can analytics and modeling help improve economic sustainability in retail supply chains?
2. What specific quantitative approaches can be used to further develop sustainable retail operations?
3. How can analytics and modeling help improve environmental sustainability in retail supply chains?
4. What are some potential benefits of using analytics and modeling in retail supply chains?
5. How can analytics and modeling help improve social sustainability in retail supply chains?
6. What types of data are most useful for analytics and modeling in retail supply chains?
7. How can analytics and modeling help identify opportunities for improvement in retail supply chains?
8. What are some potential challenges of using analytics and modeling in retail supply chains?
9. How can data analytics be used to improve retail supply chain management?
10. What are some best practices for using analytics and modeling in retail supply chains?

Step 4: Select four questions. Idea Coach drops these four questions into the BimiLeap study. The researcher can edit the questions and/or select a few questions and write in others.

Step 5: Idea Coach provides up to 15 answers for each question (refer to Table 2 in Appendix). Select four answers for each question, and/or edit the provided questions, and write in one's own questions. Table 2 shows the different answers for the four questions selected. The four selected answers for each question are inserted into the BimiLeap system almost 'as is'.

Step 6: Create a short introduction to the topic. The introduction informs the respondent about the 'meaning' of the test vignettes, or more colloquially, 'what the vignettes are all about'. The less information in the introduction or orientation, the better the study because the element will drive the respondent's ratings. The orientation reads as follows:

> *Today's stores are getting more knowledgeable about the 'supply chain'.from manufacturer to YOU. Here are things that the store does or can do. Tell us how you feel about what the store is doing. Read the whole paragraph as one 'blurb' from the store to you.*

Step 7: Create the rating scale. The rating scale will be presented along with every vignette. The respondent is instructed to read the vignette and rate the entire vignette on the scale.

The scale is left to the researcher to create. For this study, the scale comprised five anchored points, shown below. What do you feel about what you just read

1 (one) = So what ... AND ... won't deliver
2 (two) = So what ... BUT ... it could deliver
3 (three) = Can't honestly say
4 (four) = Sounds interesting ... BUT ... won't deliver
5(five) = Sounds interesting … AND ... it could deliver

Step 8: Complete the study set-up, specifying the nature of the respondents (e.g., age, gender, market, education, family structure, etc.). A third party (Luc.id, Inc., Louisiana USA) provided the respondents. The researcher or a third party can provide the respondents, e.g., a panel provider. The Mind Genomics experiment is usually finished fastest and with the fewest problems when the acquisition of respondents is contracted to the outside specialist. The time to complete the study in this project was 40 minutes from launch, and the request for respondents to obtain results was provided in an easily downloaded Excel workbook.

Step 9: Create models for the total panel relating the presence/absence of the elements to the transformed rating (this task is performed by the BimiLeap System). Recall that Mind Genomics acquires data on a Likert Scale (Step 7), but transforms the rating to a binary scale. Table 3 shows the positive coefficients for two transformed variables, R54 focusing on interest and R52 focusing on belief. The third column shows the coefficients for response time.

R54 (fifty-four) – sounds interesting (whether or not I believe it can deliver). Ratings of 5 (five) and 4 (four) transformed to 100 (hundred), ratings of 1 (one), 2 (two) and 3 (three) transformed to 0 (zero).

R52 (fifty-two) – I believe it can deliver (whether or not it sounds interesting). Ratings of 5 (five) and 2 (two) transformed to 100 (hundred), ratings of 1 (one), 3 (three) and 4 (four) transformed to 0 (zero).

To each newly created binary variable, R54 (fifty-four) and R52 (fifty-two) is added a vanishingly small random number ($<0.01\%$ or $<10^{-4}$), to ensure some marginal variation in the newly transformed variable. Even when a respondent limits the ratings to 1-3 (one to three) or to 4-5 (four to five), the newly transformed binary variable will exhibit sufficient variability so the OLS (ordinary least-squares) regression will not 'crash' due to lack of variation in the dependent variable.

The actual coefficients shown in Table 3 were submitted to a second OLS regression, this time performed manually, even though the BimiLeap system returned the OLS regression with all of the data provided by the respondents. The data on which the OLS regression was computed, and results shown in Table 3 comprised those vignettes not assigned the rating of '3 (three)', namely, only those vignettes that elicited a decision. The elimination of vignettes assigned the rating '3 (three)' was done based on the belief that one could not really count those vignettes as real votes about interest or belief, respectively. (Note that this secondary analysis is optional. The BimiLeap system already had returned Table 3, based on the ratings of ALL vignettes, not eliminating vignettes rated '3 (three)'.0 (zero)). The coefficients in Table 3 tell an interesting story or, rather several interesting stories:

1. *The additive constant for interest is high, 82 (eighty-two).*

Everyone is interested in the topic. The additive constant for belief is much lower, 49 (forty-nine), meaning that only about half the time will the respondent feel that what is being written could be real and deliver efficiencies. This high level of interest is notable, representing an unusually high additive constant for a topic unrelated to something pleasurable, like food.

2. There are virtually no elements that strongly drive 'interest'.

All of the interest ends up being contributed by the additive constant. Elements can detract from interest but not add to interest. In contrast, a number of elements strongly add to believability:

B4: By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.
A3: Analytics can help to improve communication and coordination among different stakeholders in the supply chain.
A4: Analytics can help to develop new sustainable technologies and practices.
A2: Modeling can help to identify and assess the viability of new sustainable technologies and practices.

Table 3.
Models for the total panel, excluding all vignettes rated '3' (can't honestly say)

	Total panel excluding vignettes assigned the rating '3' (can't honestly say)			
		R54	R52	RT
	Are you interested	Y	YN	
	Do you think it can deliver?	YN	Y	
	Additive constant	82	49	NA
A1	Analytics can help to identify inefficiencies and potential improvements in the supply chain.		5	0.6
A2	Modeling can help to identify and assess the viability of new sustainable technologies and practices.		8	0.5
A3	Analytics can help to improve communication and coordination among different stakeholders in the supply chain.		10	0.5
A4	Analytics can help to develop new sustainable technologies and practices.		10	0.7
B1	By understanding the customer's preferences for sustainable products, retailers can make more informed decisions about which products to stock and promote.			0.7
B2	By understanding the social and environmental impacts of the production process, retailers can make more informed decisions about which products are the most sustainable.			1.0
B3	By understanding the social and environmental impacts of the products they sell, retailers can make more responsible sourcing decisions.		4	0.7
B4	By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.		11	0.7
C1	Analytics and modeling can help identify patterns in customer behavior and demand, allowing retailers to more accurately forecast inventory needs and avoid overstocking or understocking.			0.4
C2	Analytics and modeling can help optimize pricing strategies to help improve margins and overall profitability.			0.3
C3	Analytics and modeling can help improve store layout and design to better match customer needs and preferences.			0.3
C4	Analytics and modeling can help improve transportation management to reduce shipping costs and lead times.	2	2	0.4
D1	Data analytics can be used to benchmark supplier performance, helping retailers identify the best performers and hold them accountable.		4	0.4
D2	Data analytics can be used to understand customer sentiment, allowing retailers to address concerns and improve the shopping experience.			0.4
D3	Data analytics can be used to monitor social media activity, helping retailers identify trending products and capitalize on buzz.	6		0.5
D4	Data analytics can be used to track loyalty program data, helping retailers identify and target their best customers.			0.5

3. *Response time represents a measure of engagement.*

A complex question to answer is whether a short response time (or a long response time) is essential for driving communication. All that can be said is that the short response times mean that the respondent spends little time reading the message. Note that the model or equation for response time is not estimated with an additive constant. The assumption is that in the absence of elements, the response time would automatically be 0 (zero). Here are the two fastest-read messages, requiring an estimated 0.3 seconds to read:

C2: Analytics and modeling can help optimize pricing strategies to help improve margins and overall profitability.
C3: Analytics and modeling can help improve store layout and design to match customer needs and preferences better.

In contrast, here is the slowest message, requiring an estimated 1.0 (one) second to read, more than three times slower:

B2: By understanding the social and environmental impacts of the production process, retailers can make more informed decisions about which products are the most sustainable.

Step 10: Create new-to-the-world subgroups based upon the pattern of 'interest' responses. Mind Genomics studies feature individual-level experimental designs. Each respondent evaluates the precisely correct set of test vignettes specified by the underlying design. Each respondent's data was subject to OLS regression. For clustering purposes, the dependent variable was ONLY ratings of R54 (fifty-four) (namely, interest). The independent variables were once again the 16 elements, taking the values 0 (absent from the vignette) or 1 (present in the vignette). The OLS regression generated an additive constant and 16 coefficients. Through k-means clustering, it was straightforward to generate a two-cluster and a three-cluster solution using k-means clustering (Mucherino, Papajorgji, and Pardalos, 2009). The clustering itself is a purely mathematical operation, which does not pay attention to the 'meaning' of the cluster but rather attempts to optimize specific criteria. After the clustering is performed, each respondent is assigned to one of the mutually exclusive and exhaustive clusters, called segments or 'mindsets' in the language of Mind Genomics. The two-mindset solution was hard to interpret, so the more easily interpreted three-mindset solution was used. Each cluster is homogeneous concerning the nature of the elements that perform strongly.

Finally, after each respondent was assigned to one of the three mindsets, the analysis eliminated all vignettes assigned the rating '3 (three)'. Afterward, two regression models were run, the first for each mindset, using the transformed rating of 'interest' (the variable on which the clustering was performed), and then on the transformed rating of 'believe' (the second variable, having nothing to do with the clustering.) Table 4 shows models for the three mindsets, using only vignettes not rated '3 (three)' and' 5 (five). Two models were created for each mindset, with the dependent variable of 'interest' and the dependent variable of 'believe' estimated separately. All vignettes assigned a rating of '3 (three)' were eliminated before the models were created. The patterns in Table 4 are hard to detect because of the 'wall of numbers'. The elements below are the strong performers for each mindset, first for 'Interest' and then for 'Belief'.

4.1 Mindset 1 – Focus on business efficiencies

INT C1: Sales Business Analytics and modeling can help identify patterns in customer behavior and demand, allowing retailers to more accurately forecast inventory needs and avoid overstocking or understocking.
BEL A4: Analytics can help to develop new sustainable technologies and practices.
BEL A1: Analytics can help to identify inefficiencies and potential improvements in the supply chain.
BEL A2: Modeling can help to identify and assess the viability of new sustainable technologies and practices.
BEL B4: By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.
BEL A3: Analytics can help to improve communication and coordination among different stakeholders in the supply chain.

4.2 Mindset 2 – Interested in better-running business for all stakeholders and the environment

INT D4: Data analytics can be used to track loyalty program data, helping retailers identify and target their best customers.
INT A1: Analytics can help to identify inefficiencies and potential improvements in the supply chain.
INT A3: Analytics can help to improve communication and coordination among stakeholders in the supply chain.
BEL B2: By understanding the social and environmental impacts of the production process, retailers can make more informed decisions about which products are the most sustainable.
BEL B4: By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.

4.3 Mindset 3 – Interested in metrics on customers and trends/performance of products

INT D3: Data analytics can be used to monitor social media activity, helping retailers identify trending products and capitalize on buzz.
INT D4: Data analytics can be used to track loyalty program data, helping retailers identify and target their best customers.
INT D1: Data analytics can be used to benchmark supplier performance, helping retailers identify the best performers and hold them accountable.
INT B1: By understanding customers' preferences for sustainable products, retailers can make more informed decisions about which products to stock and promote.
BEL A3: Analytics can help to improve communication and coordination among stakeholders in the supply chain.
BEL A2: Modeling can help to identify and assess the viability of new sustainable technologies and practices.
BEL C4: Analytics and modeling can help improve transportation management to reduce shipping costs and lead times.
BEL D1: Data analytics can be used to benchmark supplier performance, helping retailers identify the best performers and hold them accountable.
BEL B4: By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.

Table 4.
Models for the three mindsets, using only vignettes not rated '3 (three)'

		Interested			Believe		
	Dependent variable (all ratings of 3 eliminated before estimating the equation or model for each mind-set)	**MS1**	**MS2**	**MS3**	**MS1**	**MS2**	**MS3**
	Additive constant	95	69	72	53	67	31
	Analytics can help to identify inefficiencies and potential improvements in the supply chain.		10		13		7
	Modeling can help to identify and assess the viability of new sustainable technologies and practices.		5		12		14
	Analytics can help to improve communication and coordination among different stakeholders in the supply chain.		8		8		21
	Analytics can help to develop new sustainable technologies and practices.		7		18		6
	By understanding the customer's preferences for sustainable products, retailers can make more informed decisions about which products to stock and promote.			9			6
	By understanding the social and environmental impacts of the production process, retailers can make more informed decisions about which products are the most sustainable.			7		13	
	By understanding the social and environmental impacts of the products they sell, retailers can make more responsible sourcing decisions.		3	2	4	5	
	By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact.			3	11	11	8
	Analytics and modeling can help identify patterns in customer behavior and demand, allowing retailers to more accurately forecast inventory needs and avoid overstocking or understocking.	10					5
	Analytics and modeling can help optimize pricing strategies to help improve margins and overall profitability.	7					4
	Analytics and modeling can help improve store layout and design to better match customer needs and preferences.	7	5				3
	Analytics and modeling can help improve transportation management to reduce shipping costs and lead times.	7	5		2		14
	Data analytics can be used to benchmark supplier performance, helping retailers identify the best performers and hold them accountable.			10		7	13
	Data analytics can be used to understand customer sentiment, allowing retailers to address concerns and improve the shopping		6				4
	Data analytics can be used to monitor social media activity, helping retailers identify trending products and capitalize on buzz.		5	18			5
	Data analytics can be used to track loyalty program data, helping retailers identify and target their best customers.		12	11			6

5 Using analytics to assign new people to mind-sets about sustainability

This paper's third portion of the process involves assigning NEW people to mindsets. The notion that one can assign people to groups based on who they are or how they think is old in consumer research. Since the beginning of consumer research, the focus has often turned to differences in how people differ. By 'differ' is meant systematically differ in patterns that make sense, rather than the ever-present random variation, which is an annoying concomitant of research. The focus of work over decades has been the study of covariation, if any, between who people ARE and how people think. The data suggests that there is little clear covariation. Any patterns are error-filled at best, except for the most prominent types. Efforts to find clear patterns between the responses of mutually exclusive but parallel groups, e.g., gender, age, political affiliation, and so forth, are occasionally fruitful in the most apparent cases but are not easy to find most of the time.

Due to the ever-present yet ever-disappointing hope of easy-to-find relationships, researchers have turned to defining people not by who they are but by how they think about topics (psychographics; (Wells, 1975)). There is a better chance to find covariation between how people think about a specific topic and how people think about a granular issue. However, the agreement is only modest, perhaps because the psychographic groupings, these psychographic mindsets, are simply too diffuse.

The three mindsets emerging from the Mind Genomics studies are more specific and granular, as they should be. Rather than focusing on who the respondent IS namely, geo-demos, or how the person thinks about general topics (psychographics), a more productive way is to try to find a way to predict membership in a granular group such as the three mindsets for uncovered in this study about the retail chain. A recently published approach linked with Mind Genomics uses the pattern of coefficients for the mindsets emerging from the Mind Genomics study. The approach is called the Personal Viewpoint Identifier (PVI) (Zemel et al., 2019). The PVI approach uses decision trees and Monte Carlo methods to identify the six elements that drive the most significant difference between mindsets. The output of the PVI comprises six questions, each answered Yes/No. The pattern of the answers drives the assignment of the individual to one of the two or three mindsets, depending on how many mindsets are put into the PVI. The important thing about the PVI is that, in the spirit of AI + Mind Genomics, the tool is fast, simple, and provides a testable assignment of a person. The goal of the PVI is a 'best guess' assignment using the most straightforward data. Figure 1 shows the PVI questionnaire the respondent completed and the feedback. The data from the PVI is inserted into a database. The critical thing to remember is that, like the AI and Mind Genomics, the entire activity works at the level of the 'granular,' and is designed to be quick, approximate, and scalable. The PVI, for example, can be distributed to hundreds, thousands, or even millions of people. In a quick, 1-minute exercise, one can understand the distribution of mindsets worldwide.

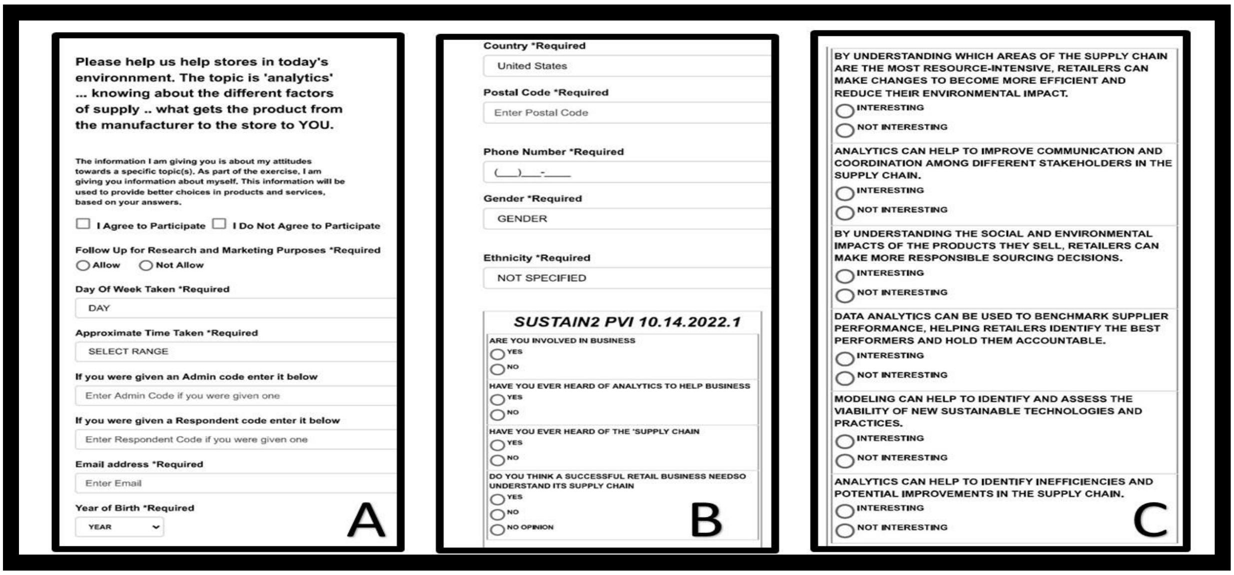

Figure 1. PVI shows the introduction (panel A), general attitude questions (panel B), and the six questions in randomized order, answers to which questions assign a new individual to a mindset (Panel C).

6 Discussion

It is a truism to say that today's world is increasingly complex, beset by major problems, often problems that suddenly emerge requiring solutions. Many of the problems are technical in nature, requiring solutions based on understanding the underlying science and technology of the issue. And then there are other issues, problems involving the understanding of people, of attitudes, and the appropriate way to communicate with people to address these issues, and by so doing, solve the emerging problem(s). It is to this latter situation that the technology in this paper is addressed. The paper was written as an investigation, or more correctly, as a demonstration, of what might be done to address a complex problem involving human decision-making and the involvement of attitudes. Rather than identifying a 'gap' in our knowledge and using science to fill that gap, namely, the common approach of 'plug a hole in the literature', we selected the phrase in the 'call for papers' and proceeded with the technology as far as possible. That phrase was: *Analytics and modeling can potentially enhance the economic, environmental, and social sustainability in retail supply chains.* This special issue aims to accelerate the development and application of quantitative approaches for problem-solving and decision-making to design sustainable retail operations. The remainder of the paper is simply the effort to create solid knowledge around the phrase above, using the phrase as a guide for artificial intelligence to create the questions and answers for Mind Genomics and the PVI (Personal Viewpoint Identifier). The stretch goal was to do the work in less than a day. The actual research effort took only a few hours, reaffirming the potential of combining AI and

Mind Genomics. In addition, we present the PVI to create actionable databases to understand people's minds on a new topic without needing to understand this topic deeply. Rather than deep understanding leading to new ideas and solutions to problems, the paper attempts to turn the process around 180 degrees, producing answers to stated problems constituting the basis for new, deep knowledge.

Acknowledgments

We thank all the participants in the Mind Genomics survey process. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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APPENDIX

Table 2.
The 15 answers for each of the four questions

	Q1: How can analytics and modeling help improve environmental sustainability in retail supply chains?
1	Analytics can help to identify inefficiencies and potential improvements in the supply chain
2	Modeling can help to identify and quantify the environmental impacts of different scenarios
3	Analytics can help to optimize the supply chain to reduce environmental impacts
4	Modeling can help to forecast future environmental impacts of different scenarios
5	Analytics can help to develop new sustainable technologies and practices
6	Modeling can help to identify and assess the viability of new sustainable technologies and practices
7	Analytics can help to monitor and evaluate the performance of sustainable technologies and practices
8	Modeling can help to compare the environmental impacts of different technologies and practices
9	Analytics can help to improve communication and coordination among different stakeholders in the supply chain
10	Modeling can help to identify and assess the risks and opportunities associated with different environmental sustainability strategies
11	Analytics can help to track and report the progress of environmental sustainability initiatives
12	Modeling can help to verify and validate the environmental benefits of different technologies and practices
13	Analytics can help to troubleshoot and optimize environmental sustainability strategies
14	Modeling can help to assess the impacts of environmental sustainability policies
15	Analytics can help to support decision-making around environmental sustainability initiatives
	Q2: How can analytics and modeling help improve social sustainability in retail supply chains?
1	By understanding which areas of the supply chain are the most resource-intensive, retailers can make changes to become more efficient and reduce their environmental impact
2	By understanding how customer behavior affects the demand for certain products, retailers can make more informed decisions about stocking levels and production planning
3	By understanding the social and environmental impacts of the products they sell, retailers can make more responsible sourcing decisions
4	By understanding the full life cycle of the products they sell, retailers can make more informed decisions about which products are the most sustainable
5	By understanding the water usage of the products they sell, retailers can make more informed decisions about which products are the most sustainable
6	By understanding the energy usage of the products they sell, retailers can make more informed decisions about which products are the most sustainable
7	By understanding the greenhouse gas emissions of the products they sell, retailers can make more informed decisions about which products are the most sustainable
8	By understanding the waste generated by the products they sell, retailers can make more informed decisions about which products are the most sustainable
9	By understanding the social and environmental impacts of the production process, retailers can make more informed decisions about which products are the most sustainable
10	By understanding the working conditions of the employees involved in the production process, retailers can make more informed decisions about which products are the most sustainable
11	By understanding the environmental impacts of transportation, retailers can make more informed decisions about which products are the most sustainable
12	By understanding the environmental impacts of packaging, retailers can make more informed decisions about which products are the most sustainable
13	By understanding the social and environmental impacts of the disposal or recycling of the products they sell; retailers can make more informed decisions about which products are the most sustainable
14	By understanding the customer's preferences for sustainable products, retailers can make more informed decisions about which products to stock and promote
15	By understanding the social and environmental impacts of their own operations, retailers can make more informed decisions about how to reduce their environmental impact

	Q3: How can analytics and modeling help improve economic sustainability in retail supply chains?
1	Analytics and modeling can help identify patterns in customer behavior and demand, allowing retailers to more accurately forecast inventory needs and avoid overstocking or understocking
2	Analytics and modeling can help optimize pricing strategies to help improve margins and overall profitability
3	Analytics and modeling can help improve store layout and design to better match customer needs and preferences
4	Analytics and modeling can help improve supply chain management to reduce waste, inventory costs, and lead times
5	Analytics and modeling can help improve marketing strategies to better target potential customers and promote loyalty
6	Analytics and modeling can help improve employee training programs to reduce turnover and improve retention
7	Analytics and modeling can help improve store operations to reduce costs and improve efficiency
8	Analytics and modeling can help improve customer service to reduce complaints and increase satisfaction
9	Analytics and modeling can help improve loss prevention strategies to reduce shrinkage and theft
10	Analytics and modeling can help improve facilities management to reduce maintenance costs and improve uptime
11	Analytics and modeling can help improve sustainability initiatives to reduce waste and increase recycling
12	Analytics and modeling can help improve security protocols to reduce the risk of theft or vandalism
13	Analytics and modeling can help improve inventory control to reduce stockouts and obsolescence
14	Analytics and modeling can help improve transportation management to reduce shipping costs and lead times
15	Analytics and modeling can help improve data management to improve decision-making and operational efficiency
	Q4: How can data analytics be used to improve retail supply chain management?
1	Data analytics can be used to identify patterns in customer behavior that can help optimize stock levels and reduce out-of-stocks
2	Data analytics can be used to forecast customer demand more accurately, which can help retailers better manage their inventory levels
3	Data analytics can be used to identify which products are selling well and which are not, which can help retailers adjust their product mix
4	Data analytics can be used to identify which SKUs are selling well in which stores, which can help retailers better allocate inventory
5	Data analytics can be used to identify which stores are selling more of certain products, which can help retailers better target their promotions and marketing
6	Data analytics can be used to monitor supply chain performance, identifying areas of improvement and inefficiency
7	Data analytics can be used to benchmark supplier performance, helping retailers identify the best performers and hold them accountable
8	Data analytics can be used to monitor order accuracy and identify errors, helping to improve the accuracy of future orders
9	Data analytics can be used to track delivery times and performance, allowing retailers to improve their fulfillment processes
10	Data analytics can be used to evaluate returns data, helping retailers identify problem products and areas for improvement
11	Data analytics can be used to understand customer sentiment, allowing retailers to address concerns and improve the shopping experience
12	Data analytics can be used to monitor social media activity, helping retailers identify trending products and capitalize on buzz
13	Data analytics can be used to analyze web traffic data, helping retailers identify areas of the site that need improvement
14	Data analytics can be used to track loyalty program data, helping retailers identify and target their best customers
15	Data analytics can be used to identify opportunities for cross-selling and upselling, helping retailers increase sales and profits