Journal of
Health & Medical Informatics

Abdel-Hamid, J Health Med Informat 2016, 7:3
DOI: 10.4172/2157-7420.1000228

Research Article | Open Access

# Mi Volumetrics: Smarter Diet Composition through Optimization

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**Abstract**

Poor dietary adherence has been implicated as a primary contributor to the (stubbornly) low success rates of long-term weight loss maintenance. In this paper, I argue that smarter diet composition (through computer-supported optimization) could help increase the chances of long-term success (and a healthy outcome) by allowing dieters customize meal plans that conform to personal preferences and needs (e.g., for things like taste, affordability, fat content).

Because of the large variety of food choices available and multiple/conflicting nutritional tradeoffs, tailoring meal composition is both combinatorially and computationally complex (where doing the obvious thing does not necessarily produce the obvious, desired outcome). Luckily, that's precisely where computer tools can help allowing us to combine the strengths of the dieter with the strengths of the computer. The dieter specifies alternatives, preferences and requirements and the computer then sifts through the messy maze of possibilities/tradeoffs to pick the optimal choice.

Mi Volumetrics a decision-support tool to help lay dieters optimize meal planning—combines three resources: a lay-friendly user interface, an extensive database of food options to select from and an optimization engine for customizing meal selection. By optimizing is meant designing meals that are: (1) Satiating to the individual dieter; (2) Include only food items that she/he likes (or can afford); and (3) Meet any other personal health requirements (e.g., a ceiling on the amount of calories from fat). To make the Mi Volumetrics tool widely accessible it is built in Microsoft Excel --- a software package that most people have access to and experience using.

**Keywords**: Obesity; Dieting; Customization; Optimization; Spreadsheet modeling

## Calories-wise Grams-foolish

The evidence on long-term dieting performance and weight loss maintenance remains discouragingly consistent: success rates continue to be stubbornly low—at around 20% [1]. A primary contributor to the low success rate, health care professionals and academics have long contended, is poor dietary adherence [2-4].

When it comes to meal planning, most dieters, it seems, fall victim to a "calories-wise grams-foolish" trap. They fret over setting weight-loss goals and calculating caloric targets, but give little thought to designing smart (satisfying) meals. For example, a common practice is to cut caloric intake by simply consuming less of the foods they are currently eating… and become resigned to feeling hungry and deprived [5]. It's not a recipe for success.

Diets that induce deprivation almost always fail in the long run because they ignore the basic fact that people like to eat. A deprived dieter just winds up hungry and unhappy and before too long reverts back to his/her old ways.

It doesn't have to be that way. The "grams-wise" insight of *volumetrics [5]* is that, by being smart about food selection, a dieter can cut calories while staving hunger. By decreasing the energy density of foods, people can eat enough (grams of food) to feel satiated (sometimes even eat more than they have been) while still slimming down.

Experimental studies have demonstrated that (to our bodies) food bulk, not caloric content, has the overriding influence on satiety-that is, on what makes us feel full. Food bulk, not energy content, in other words, is the key to what makes our bodies say we've eaten enough. Thus, by consuming low-energy-dense foods we can maintain the meal size that satiates us while decreasing caloric intake-allowing dieters to lose the weight without the deprivation!

One way to decrease energy density is to select foods which have higher water content. Because water increases food volume without adding calories, foods which have high water content, such as vegetables and fruit, cause us to feel full on fewer calories and lead to reduced energy intake. After water, fiber contributes the most to food volume for the fewest number of calories, supplying 1.5 to 2.5 calories per gram. In contrast, dietary fat is the most energy-dense macronutrient, containing more than twice as much energy per unit weight than either protein or carbohydrate (nine calories per gram for fat versus four calories per gram for both proteins and carbohydrates).

And here is the really good news: even modest changes in energy density can have an appreciable impact.

"For example, on a typical day an adult might consume 1200 g of food with an overall energy density of 1.8 kcal/g, giving an energy intake of 2,160 kcal. If the average energy density of the diet was decreased by 0.1 kcal/g while the same weight of food was consumed, then the individual would ingest 2,040 kcal. Thus, a relatively small change in the overall energy density of the diet would reduce energy intake by 120 kcal per day" [6].

That's not an insignificant drop in daily caloric intake. Research studies have indicated that most people tend to put on weight at the slow rate of two pounds a year [7]. This suggests that, for most people, obesity results from a strikingly small but sustained energy imbalance, [8] estimate that, "most of the weight gain seen in the population could be eliminated by some combination of increasing energy expenditure and reducing energy intake by100 kcal/day."

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**Received** October 06, 2015; **Accepted** May 11, 2016; **Published** May 18, 2016

**Citation:** Abdel-Hamid TK (2016) Mi Volumetrics Smarter Diet Composition through Optimization. J Health Med Informat 7: 228. doi:10.4172/2157-7420.1000228

In this paper, I propose taking the volumetrics strategy one step further: to a more customized "Mi Volumetrics." Besides juggling calories and energy densities, dieters would increase the chances of long-term success (and a healthy outcome), I contend, by composing meal plans that conform to personal preferences and needs (e.g., for things like taste, affordability, fat content).

The trend towards customization is, of course, taking root in a wide range of industries. Rather than continuing to mass produce for the increasingly elusive "average customer," many businesses are already using state of the art information technology to build and deliver products and services designed to fit the precise specifications of each individual customer. As consumers, we expect custom solutions/products in more and more of the things we do and buy, and now it needs to happen in health. Indeed, it is in our health where customization may return its greatest dividend.

The ticket, many in public health believe, is the growing and synergistic entwinement of the healing and information technologies. Computer-technology is changing the economic rules of health prevention and enabling customization and interactive communication both technically and economically [9]. And the Internet provides an efficient electronic infrastructure for delivering the new generation of information-based tools for personal health management and for doing it affordably for large numbers of people.

But is customizing meal planning an everyday activity that most people are intimately experienced with a computationally "worthy" task that deserves computing support? I believe the answer is yes.

It seems paradoxical, but optimal food selection in our modern environment of food abundance is no lark. The large variety of food choices available to us, while undoubtedly a blessing can also make choosing a diet unbearably confusing (In The Paradox of Choice, Barry Schwartz convincingly argues that choice overload, a phenomenon that applies to many common decisions not only to food selection, complicates decision-making because it tends to increase uncertainty and frustration). Indeed, research studies of supermarket shoppers consistently show they often feel overwhelmed by the information they have to process.

"Americans Find Doing Their Own Taxes Simpler than Improving Diet and Health" blared a recent headline in ScienceDaily, the reputable online journal. According to a recent study, 52% of Americans think doing their taxes is easier than figuring out what to eat to be healthy. Of course, part of the problem is that we have so many food choices. Choosing becomes overwhelming ("Americans Find Doing Their Own Taxes Simpler than Improving Diet and Health," http://www.sciencedaily.com/releases/2012/05/120523145655.htm).

Besides grappling with the large variety of food choices, multiple/conflicting nutritional tradeoffs (e.g., calories, bulk, and macronutrient composition) further complicate the design task. Indeed, best-mix type problems with conflicting tradeoffs can be particularly insidious since doing the obvious thing does not produce the obvious desired outcome.

Luckily, that's precisely where computer tools can help. To demonstrate, let's consider a hypothetical (though not atypical) dieter's scenario.

## The "X" Scenario

Our scenario's protagonist is a hypothetical 50 year old female office worker we'll call Ms. "X." Her personal characteristics are as follows:

Sex : Female

Age : 50 years

Current Weight : 75 kg

Height : 1.5 meters

BMI : 33

Fat% : 30%

Her base-line caloric intake is 2,500 kcal/day (composed of food items with an average energy density of 1.5 kcal/g). That's the current level of food intake that: (1) Satiates her; and (2) Has maintained her at 75 kg weight. We'll further assume that Ms. "X" eats three meals a day with caloric allocations among the three meals that are as shown in Table 1.

With a body mass index (BMI) of 33, our hypothetical Ms. "X" realizes she is overweight and decides to go on a diet to cut down on her current (steady state) caloric intake of 2,500 kcal/day.

While her new diet plan will in all likelihood involve changes to all three meals, for the remainder of our discussion we will focus on just one, namely, lunch. Treatments of breakfast and dinner would essentially be the same.

As indicated in Table 1, the energy density of her pre-dieting satiating lunch is assumed to be 1.5 kcal/g (Energy density is the number of calories in a specified amount of food. It is generally presented as the number of calories per gram of food kcal/g). This suggests that a 600 g lunch is satiating for her.

As will be discussed later, for most people, satiation level is not characterized by just a single number (e.g., for Ms. "X" exactly 600 g). Rather, most people are perfectly content (and indifferent) consuming meals that fall within a gratifying margin—referred to as the satiated margin. When we eat meals that fall within our satiated margin we feel fine (content) and are indifferent of the small differences.

For Ms. "X" we'll assume that the range of lunch sizes that satiate her is 600-1,000 g. The minimum threshold of the range 600 g—is the critical number here since it designates the minimum threshold below which she would remain hungry after consuming the meal.

## Energy Density (E.D.) Plot

Before charting a new nutritional course to lose the weight, it would helpful for Ms. "X" (indeed most dieters) to first assess where she stands. Mi EDPP-Mi Energy Density Polar Plot --- is a graphical tool available within the Mi Volumetrics tool kit to provide prospective dieters with a "big picture" type assessment of where they currently stand nutritionally and also intimate promising direction(s) for improvement. Mi EDPP integrates into one compact graphic three key nutritional parameters, namely, energy density, total meal weight (the key determinant for what makes a dieter feel satisfied) and total calories (the key to weight loss/gain). As we'll see, it is handy tools that can help Ms. "X" not only visualize where she stands but also "nudges" her towards the optimal path forward.

| Base-line meals | Calories | Energy density (kcal/g) |
|---|---|---|
| **Breakfast** | **450** | **-** |
| **Lunch** | **900** | **1.5** |
| **Dinner** | **1150** | **-** |
| Total | 2500 | - |

**Table 1:** Ms. "X" caloric allocations among daily meals.

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Ms. X's Mi EDPP is shown in Figure 1. In Mi EDPP, distance from the pole/center designates a meal's weight in grams. Thus, meals that have the same weight would all fall on the same circle. As shown, the scale on the vertical axis provides for weights that range from 0-1,000 g. In the figure, the 600 g circle is highlighted for good reason it demarcates the minimum threshold of Ms. X's satiating margin.

Energy density determines where on the circle a particular food item would fall. Energy density is measured by the size of the angle from vertical (like hours on a clock). Starting at the top (the 12 O'clock position) is zero energy density and as we travel around the plot in a clockwise direction energy density increases. Figure 1 shows energy density values starting at zero at the top and increasing in increments of 0.25 kcal/g until we reach 4.75 kcal/g when we complete one rotation. Lines radiating out from the center of the circle are thus constant energy-density radials. The intersection of an energy density radial and a weight circle designates the meal's caloric content. As shown in Figure 1, Ms. X's pre-diet 900 calories lunch falls at the intersection of the 600 gram circle and the 1.5 kcal/g energy density radial.

If we assume that the energy densities of the food stuffs she likes to consume for lunch are around 1.5 kcal/g (with some items slightly above and otherwise slightly below) and that her satiation margin is 600-1,000 g, then her current lunch selections would cluster within the shaded oval in Figure 1 (along the 1.5 kcal/g radial on the section between the 600 and 1,000 g circles).

Finally, besides weight and energy density, it would be useful (necessary) to also demarcate her meals' caloric contours since total calories are the key to weight loss/gain. Plotting meals with equal caloric content produces the hockey-stick-shaped iso-calorie curves. With that plotted, Ms. X's pre-diet satiating lunch is now fully characterized at the intersection of the 600 g circle, the 1.5 kcal/g energy density radial and the 900 kcal iso-calories curve.

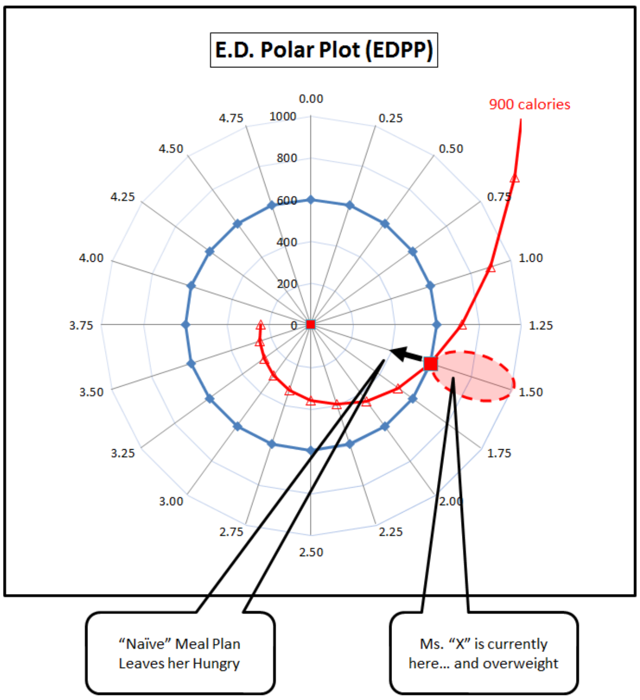


**Figure 1:** Mi EDPP.

As was mentioned, Ms. "X" decides to go on a diet and cut down on her daily caloric intake to lose weight. We'll assume that she figures she needs to cut her caloric intake for lunch from 900 to 600 kcal (Later, I will discuss how to determine total and meal-wise daily caloric levels to achieve weight-loss targets). For now, the question she needs to address is this: composing a 600 kcal lunch that works "best" for her? There are, obviously, countless possibilities. Indeed if she were to plot what food options are available to her in her neighborhood's grocery store the options would completely jam-pack her Mi EDPP chart.

As mentioned earlier, a common naïve practice is to cut caloric intake by simply consuming less of the foods one is currently eating. That would move Ms. "X" towards the pole in the direction of the black arrow (along the 1.5 kcal/g density ray in Figure 1). Such a meal (which would measure 400 g in weight) would fall within the hungry circle (because it is below her 600 g threshold) leaving her feeling hungry and deprived. Which doesn't bode well for her long-term prospects.

There is a better way.

## Not Thinking Straight... Thinking in Circles

The volumetrics strategy suggests a better nutritional path would be to move along her satiating circle (the new black arrow in Figure 2) rather than along the energy density ray. More specifically, her Mi EDPP would help her recognize how she needs to "change lanes" move from the 900 to the 600 iso-caloric hook. And once there, she needs to move along the segment of the 600 iso-caloric curve that's on the outside of the 600 g circle (her minimum threshold for satiety). That is, she needs to compose meals that fall along the green arrow in Figure 2.

Designing meals that fall within the narrow band of the green arrow dramatically reduces the number of options she needs to consider and, thus, appreciably simplifies her meal planning task. Appreciably but not totally. Why? Even within the narrow band of options demarcated by the green arrow—lunches that are above 600 g in total weight and with an average energy density between 0.75 and 1.0 kcal/g—she is still left with a host of variables to juggle. For example:

1. As with a jigsaw puzzle, a meal is typically composed of more

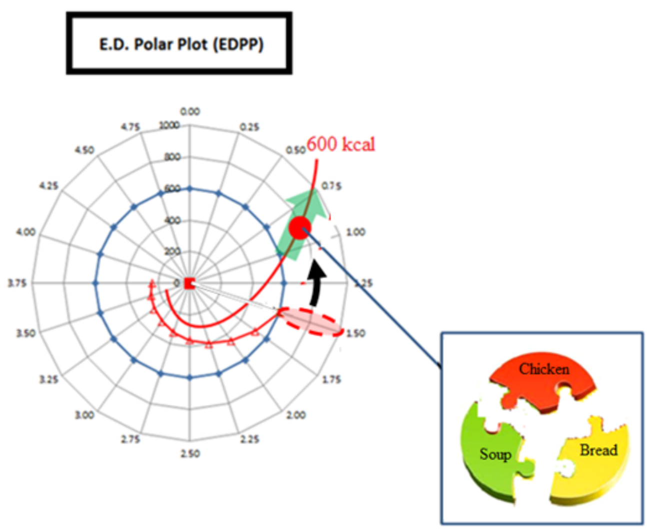


**Figure 2:** Where Ms. "X" stands and where she needs to go.

than one food item sometimes many more. This means there will be many options to mix and match when composing meals that meet particular targets such as energy density. For example, picking an energy density target within the designated range of 0.75-1.0 kcal/g, say 0.8 kcal/g does not mean picking only food items with exactly that value. Rather, she can pick some food items with higher energy density some with lower as long as the average of the entire meal is 0.8 kcal/g. This provides flexibility, of course, but also complicates the selection task.

2. In addition to weight, caloric content, and energy density, our stated (ambitious) goal is to compose optimal meals that also reflect her personal preferences (e.g., for things like taste, accessibility, and affordability). This adds additional personalizing dimensions that need to be factored in. And is why Mi Volumetrics employs elaborate templates to enter the user's food preferences and the option to specify "Must Have" items.

3. If needed or necessary, there could be additional requirements to satisfy (such as to limit the amount of fat or carbohydrate calories in the diet).

And she needs to accomplish all of that while sifting through a vast database of hundreds of different food items!

Ms. "X" has a classic problem on her hand… a problem of optimization.

## Intuitive (sub) Optimization

To demonstrate the need for and utility of optimization tools for even simple selection tasks, I report below results of an informal meal optimization exercise we've been conducting annually (since 2010) in the kick-off lecture of our Decision Analysis course at the Naval Postgraduate School. However, rather than ask the students to select from hundreds of food items (as a real life dieter might) we present them with a much smaller seven-item menu. Specifically, the students are asked to tackle the following exercise: select from a given set of seven food items a meal that maximizes total meal weight without exceeding 1,500 calories (Table 2).

| Food item | Calories | Weight |
|---|---|---|
| Pizza, thin crust, pepperoni | 500 | 160 |
| McDonald's French Fries | 250 | 80 |
| McDonald's apple Pie, Baked | 350 | 100 |
| KFC chicken breast | 600 | 200 |
| Ice cream cone, Choc covered | 700 | 220 |
| Fish, Kind salmon | 450 | 120 |
| White cake with frosting | 300 | 80 |

**Table 2:** Seven food options.

The seven food items and their characteristics are shown in Table 2

What would be that optimal meal?

Over the years our students' performances have been remarkably consistent and, we suspect, representative of what most dieters would do. What we have found (and is consistent with what other researchers have as well) is that in dealing with such seemingly simple "what's best" problems, decision-makers invariably rely on "rules of thumb" or "heuristics" rather than cumbersome math. Heuristics are convenient (occasionally sufficient) mental short-cuts we routinely rely on in many judgmental tasks we face to simplify our world. Indeed, it almost seems to be part of human nature [10]. These mental shortcuts are an efficient quick-and-dirty strategy that helps us reduce mental effort and speed up the process of finding satisfactory solutions most of the time. Unfortunately, these "short-cuts" can lead to systematic errors in certain cases. As they do here.

For many of our students, a common (and perfectly reasonable) approach is to sort the foods in the list (some sort by calories others by weight or energy density) and then go through the list top-to-bottom picking food items until the total caloric target is reached.

Table 3 shows the solution that would be selected when the seven food items are sorted by energy-density (the most common approach):

Not bad… but it is not the best (optimal) meal. (Nor are the solutions derived when the food items are sorted by weight or calories.) In this case, the student/dieter sorts the seven food items by energy density (from the lowest item #4 to highest item #7) and then, starting at the top, proceeds to select foods on the list (while cumulatively adding the total number of calories) until they hit the caloric ceiling. This leads to the selection of food items #4, 1, and 2.

- It produces a meal with a total weight = 440 g and with 1,350 total calories.
- The meal's weight cannot be increased further without exceeding the 1,500 caloric target since all remaining food items (#5, 3, 6, and 7) pack more than 150 calories.

Again, not bad… but (as noted) there is a better solution which uses the caloric budget more effectively!

But it requires a proper optimization tool (such as the Mi Volumetrics to be discussed shortly) to derive it. The optimal solution selects food item 3 instead of item 2. By selecting food items 4, 1, 3 we compose the optimal (most satisfying) meal for the dieter: with a total weight of 460 g and a total caloric content of 1,450 kcal.

In this class exercise, the suboptimal solution is not that far off, but that's only because the problem is overly simplified with only seven food items (not hundreds). As the problem gets bigger, the divergence between what's optimal and what's not grows… and the stakes will be higher.

| Food item | Calories | Weight | E.D | Cum cal | | Cum wt |
|---|---|---|---|---|---|---|
| Kfc chicken breast | 600 | 200 | 3 | 600 | | 200 |
| Pizza, thin crust, pepperoni | 500 | 160 | 3.13 | 1,100 | | 360 |
| Mcdonald's apple pie, Baked | 250 | 80 | 3.13 | 1,350 | | 440 |
| Ice cream cone, Choc covered | 700 | 220 | 3.18 | 2,050 | | - |
| Mcdonald's French fries | 350 | 100 | 3.5 | 2,400 | | - |
| Fish, kind salmon | 450 | 120 | 3.75 | 2,850 | | - |
| White cake with frosting | 300 | 80 | 3.75 | 3,150 | | - |

**Table 3:** Solution when sorting by energy density.

The bottom-line "lesson" of lecture 1: when it comes to optimization-type problems, better not to listen to our gut. The intuitive approach often fails us.

Luckily, that's precisely where computer tools can help. Computer modeling is well suited to fill the gap where human cognition is taxed, allowing us to combine the strengths of the dieter with the strengths of the computer. The dieter specifies alternatives, preferences and requirements and the computer then sifts through the messy maze of possibilities to pick the optimal choice.

With this in mind, let's now pursue the more real-life-like scenario of a dieter grappling with hundreds (not just seven) food items to demo the application and utility of Mi Volumetrics—a decision-support tool we developed to help lay dieters optimize meal planning.

## The Mi in Mi Volumetrics

To do that, we will use the tool to design the optimal lunch for Ms. "X"—our hypothetical dieter. Specifically, our task is to help Ms. "X" select from her personal subset of desirable foods a mix of food items that maximize her lunch's bulk (and thus her satiety) without exceeding the caloric target she sets for losing weight.

Successful dieting necessitates doing at least three things well [11]: (1) Setting a realistic weight-loss goal; (2) Determining the proper (individually-tailored) caloric deficit to achieve it; and (3) Devising a palatable and satisfying diet that can be sustained (our focus in this paper).

We'll assume Ms. "X" sets a weight-loss target to lose 7.5% of her weight in 3 months. To determine the caloric deficit to lose the weight, most dieters would turn next to the ubiquitous weight-loss rule (also known as the 3,500 kcal per pound rule). This 3,500 kcal per pound rule continues to be the staple energy calculus by which dieters (as well as many health care professionals) explain weight gain and predict treatment outcomes. A serious mistake!

As argued in greater detail elsewhere [12], the 3,500 kcal per pound rule is a crude tool that does not (cannot) reliably predict treatment outcomes. The 3,500 kcal per pound rule gets it wrong, in large part, because it is a static predictor that ignores the dynamic physiological adaptations to altered body weight the involuntary homeostatic adaptations that lead to changes of both the resting metabolic rate as well as the energy cost of physical activity [13]. It is also a "one-size-fits-all" model that overlooks the fact that responses to weight-loss interventions vary a great deal among individuals (due to differences in body composition). Reliance on such simplistic one-size-fits-all tools—justifiable perhaps in the pre-Internet ages when we were computationally poor is a bankrupt strategy that must be abandoned in favor of more dynamic and more intimate tools that actually fit.

Thanks to the great advances in medicine and computational sciences over the last few decades, we now have the dynamic models that allow us to predict with great fidelity how the human body regulates its energy and mass [13,14]. And thanks to the availability of affordable, high-quality computing capabilities we can easily (and economically) tailor these tools to each person's "specs" and lifestyle preferences (what they prefer to do or not do). Mi Model—a system dynamics model that's part of the Mi Toolkit is such a tool [11,14].

We'll assume Ms. "X" uses Mi Model to set the caloric target for losing 7.5% of her weight in 3 months. As explained elsewhere [11], Mi Model's recommended caloric target for Ms. "X" is: To cut daily energy intake to 8.4 mega joules (MJ) = 2,000 kcal (which amounts to a 20% cut to her current food intake level).

The daily caloric intake of 2,000 calories needs to be allocated among her three meals. Following the typical meal allocations proposed in Barbara Rolls' volumetrics books (20% to breakfast, 30% to lunch and 50% to dinner), Ms. "X" allocates 600 kcal for her lunch.

With weight-loss and caloric targets set, her final planning step is to design her palatable and satisfying meals.

Generally speaking, composing a 600 kcal lunch is no big deal. But that's not what we are after. What we seek to accomplish is much more ambitious and is much more personalized: to design the "optimal" lunch for Ms. "X." By optimal I mean a lunch that:

- Is also satiating to her.
- Includes only food items that she likes (or can afford).
- (If needed) meets any other personal requirements (e.g., a ceiling on the amount of calories from fat).

Composing such a meal is not only significantly more challenging, but is also very personal. For example, what satisfies Ms. "X" might not satisfy you or me? Which is why identifying her preferences is where we need to start. There are several, but first and foremost we need to identify what meal size (weight) satiates her (the top bullet above). Once we establish this important threshold (and what will be important here is the minimum satiation threshold), we can then proceed to compose the optimal mix of food stuffs that meet her caloric target and any other preferences or requirements.

## The Satiation Margin... it's personal

We've already learned that a meal's weight, not energy content, is the key to what makes our bodies say we've eaten enough. Thus, the question for Ms. "X" (and any prospective dieter): what is the lunch weight that satisfies? The answer is neither obvious nor universal—it will differ from person to person.

Research by Dr. Brian Wansink and his group at Cornell University's Food and Brand Lab suggests that a person's satiation level is not characterized by just a single number (say 800 g). Rather, Wansink [15] and his team found that most people are perfectly content (and indifferent) consuming meals that fall within a gratifying margin and which for most people is approximately 20% above to 20% below their so called nominal satiation level. They called this range the satiated margin. When we eat meals that fall within that weight range our satiated margin we feel fine (content) and are indifferent of the small differences.

Figuring out one's satiated margin (e.g., for a lunch meal) is an empirical issue. But isn't that difficult to assess. It simply requires experimenting with meal sizes that satisfy us and measuring/recording their weights. To increase the reliability of and confidence in our assessment and because we seek to determine a range one would need to collect multiple data points, say two weeks' worth. After each lunch, one of two methods may be used to assess the meal's total weight: (1) Physically weighing the meal (e.g., using a food scale); or (2) Using Mi Volumetrics. With the latter approach, one would simply need to enter the food items into the Mi Volumetrics spreadsheet (as demonstrated next) and use its built-in weight-calculator to compute the meal's total weight.

Let's assume Ms. "X" obliges and after fourteen lunch experiments determines that the range of lunch sizes that satiate her are from 600-1,000 g. The minimum threshold of the range 600 g is the critical number here since it designates the minimum threshold below which

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she would remain hungry after consuming the meal.

## System Architecture

Mi Volumetrics is a tool that combines three resources: a user interface, an extensive database of food options to select from and an optimization engine for optimizing meal selection (Figure 3). The database of food options is derived from the database of over 600 items compiled by Barbara Rolls and Robert Barnett in their book, The Volumetrics Weight-control Plan. For each food item, Rolls and Barnett provide information on serving sizes, calories per serving, and energy density. In Mi Volumetrics, the Rolls/Barnett data is augmented with additional metrics on total weight per serving (in grams) and macronutrient composition (fat, carbohydrate, protein and fiber) gleaned from the USDA national Nutrient Database (The USDA National Nutrient Database for Standard Reference [SR] is the major source of food composition data in the United States. It provides the foundation for most food composition databases in the public and private sectors).

To make the Mi Volumetrics tool widely accessible to the general public it is built in Microsoft Excel—a software package that most people have access to and experience using. Mi Volumetrics is freely downloadable at: http://www.bookhealthybytes.com/software.html

## Deploying Mi Volumetrics

At this point, Ms. "X" has already accomplished two necessary preparatory steps:

1. Determined her daily energy intake target at 2,000 calories (using Mi Model). And based on that, determined her desired caloric allocations among the three meals to be: 400 calories for breakfast, 600 for lunch and 1,000 for dinner.
2. To compose her optimal "palatable and satisfying" lunch, she has also determined that her minimum satiating threshold for lunch is 600 g (and her satiating margin: 600–1,000 g).

With this in hand, she is now ready to deploy Mi Volumetrics to design her optimal meal. It is a three step process (A, B and C):

A. Use the Mi Volumetrics' food selection templates to enter food candidates. In this first sub-step, it is important to note, she is not yet designing the meal, rather she is casting a wide net to include all desirable food candidates that may be used to compose her lunch. The more food candidates she enters here, the wider the net she casts and the more helpful the program will be.

To facilitate the search for/and selection of food items, the database of 600 food items is organized into food categories such as "Breads and Grains," "Cereals," "Fruits," "Beverages," etc. (Figure 4). Each category, in turn, contains many food items. For example, the "Breads and Grains" category contains 57 entries of food items such as: bagels, French bread, rye, sourdough, etc.

To search for/and select food items, Ms. "X" would go through the list of food categories one at a time and,

- From each category, pick the food item she would like to be considered (e.g., Plain Bagel in "Breads and Grains" or Diet Cola in "Beverages"). This is done by simply clicking on the empty cell adjacent to a category of interest. When a category's empty cell is clicked, a sub-menu showing the category's list of food options will open up from which an item may be selected. Figure 4 shows the sub-menu of food options that opens up when the user clicks on the entry cell for "Breads and Grains." The seven items shown in Figure 4 are just the top seven entries from a list of 57 food items within the "Breads and Grains" category. To see the rest, one simply scrolls down the list.
- Once the user finds the "Bread and Grains" food item they would like to select (say French bread), they would click on it to enter it as their selection. When the selection is made, a

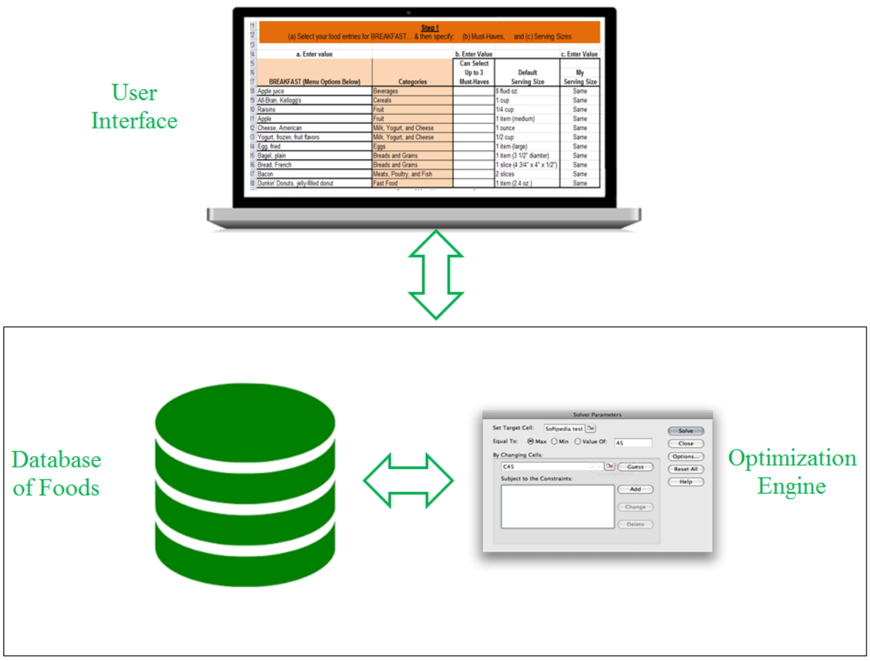


**Figure 3:** Mi volumetrics architecture.

default serving size will automatically be displayed (e.g., the default serving size for soup in the "Soups" category is "a cup of soup"). If this default serving size is the right serving size, nothing further needs to be done for that entry. If not, the user can adjust it (for example, doubling or tripling the serving size).

- The user may (but doesn't have to) designate up to 3 food entries as "MUST HAVES." The program will oblige by forcing these to be included in the optimal solution.
- For some categories (e.g., Meats), the user is allowed to enter two entries. This allows the user to specify more options. The program assumes that while the user requires that all such options to be considered only one should be included in the final menu. If desired, however, the user can override this default assumption to allow both entries in a category (such as two "Meats, Poultry, and Fish") be included (Table 4).

B. In the second sub-step, the user specifies the constraints that her optimal meal needs to satisfy. Constrains are certain performance criteria that the optimal meal must meet. There are at least two:

- The meal's total weight needs to equal or exceed her minimal satiating threshold. In this case, her meal's weight needs to equal or exceed 600 g.
- The meal's total caloric content needs to equal or be less than her caloric target. In this case be equal to or less than 600 kcal.

When the user is done entering her food selections and constrains, built-in macros automatically map the user's inputs (using excel functions like VLOOKUP) into an "Optimization Model Input Table" suitable for the Excel's Solver to work on. A partial "Optimization Model Input Table is shown in Table 5.

C. In the third and final sub-step, the user executes the Mi Volumetrics optimization function to compose her optimal lunch. The underlying optimization model is an Integer (binary) linear programming model with the following formulation:

- The objective function is defined to maximize meal weight.
- The decision variables are the food items selected. To keep track of which food items are chosen, the model uses a binary (0-1) variable for each food item. If a particular food item is chosen, the 0-1 variable for the food item will equal 1; if it is not chosen, the 0-1 variable will equal 0.
- The constraints include: A ceiling on the meal's total caloric content and lower threshold on the meal's total weight in grams (Other constrains—such as fat content may be incorporated as well) (Figure 5).

Running the optimization function is easily accomplished by clicking a "Run Optimization" button (which automatically activates a built-in macro). Mi Volumetrics, will then display the optimal solution. Below in Table 6 is an example optimal meal composed by the model (showing the meal's six selected food items and their servings).

As shown in Table 6, the optimal lunch's total weight is 836 g (right in the middle of Ms. X's satiating margin) and its total caloric content is 569 (below her target ceiling of 600 kcal). Furthermore, it is a meal composed of food items she likes. Ms. "X" has just composed her optimal lunch!

Because the Mi Volumterics' database (and model) has been augmented to incorporate additional nutritional data elements, Ms. "X" can utilize the tool to accomplish even more. For example, as shown in Figure 6, Mi Volumetrics can provide Ms. "X" with a breakdown of the macronutrient content of her optimal meal. Proper nutrient composition is paramount to maximize energy level, well-being, and overall health. Which is why tracking the nutritional composition of our food intake is always important but is especially so when dieting. On a diet we are eating less, thus we are at a higher risk of not getting an adequate amount of nutrients. Below is the macronutrient composition of Ms. X's optimal meal.

Upon displaying the macronutrient composition, Ms. "X" can then re-deploy Mi Volumetrics to customize her optimal meal even further e.g., to design meals that achieve additional objectives. Indeed, that's precisely where optimization-type models are really at their best allowing us to explore (and devise) new and better strategies when pursuing our goals. For example, the Mi Volumterics tool can be utilized to design meals that do not exceed targets for fat- or carbohydrate-derived calories or that include a minimum amount of fiber (e.g., to satisfy health-related dictates).

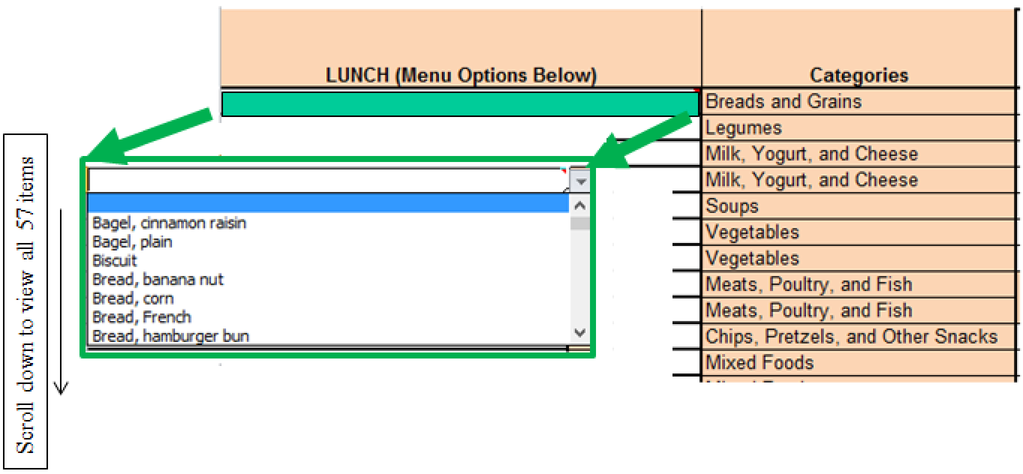


**Figure 4:** Template to enter food selections.

| | **b-Keep Default Settings: Only 1-of-Kind entry to include** | **c-Enter Value** | - |
|---|---|---|---|
| Categories | To over-ride and allow both (meat/fruit/dessert) entries, change setting below | Can Select up to 3 Must-Haves | Default Serving Size |
| Breads and Grains | - | - | 1 item (6 1/2 daily) |
| Legumes | - | - | 1/2 cup |
| Milk, Yogurt, and Cheese | Only 1 Meats entry to include. To allow both, change setting below. | - | - |
| Milk, Yogurt, and Cheese | | - | - |
| Soups | - | - | 1 cup |
| Vegetables | - | - | 1 cup |
| Vegetables | - | - | 1 ounce |
| Meats, Poultry, and Fish | - | - | 3 oz |
| Meats, Poultry, and Fish | - | - | - |
| Chips, Pretzels, and Other snacks | - | - | - |
| Mixed Foods | - | - | - |
| Mixed Foods | - | - | - |
| Fast Food | Only 1 Fast Foods entry to include. To allow both, change setting below. | - | - |
| Fast Food | | - | - |
| Condiments, Dressings, and Sauce | - | - | - |
| Condiments, Dressings, and Sauce | - | - | 1 item, 3 3/4" long |
| Beverages | - | - | 4 fluid oz |
| Fruit | Only 1 Fruits entry to include. To allow both, change setting below. | - | |
| Fruit | | - | 1 iem (medium) |
| Desserts | Only 1 Desserts entry to include. To allow both, change setting below. | - | - |
| Desserts | | - | - |
| Candy | - | - | - |
| To override Default Change to "Allow 2-of kind" => | Only 1-of-Kind | 0 (3 or Less) | - |
| | | | - |

**Table 4:** Specifying food selections.

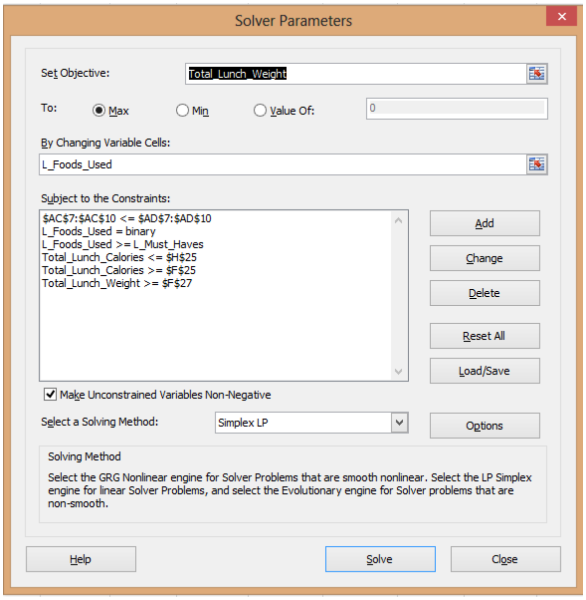


**Figure 5:** Solver menu.

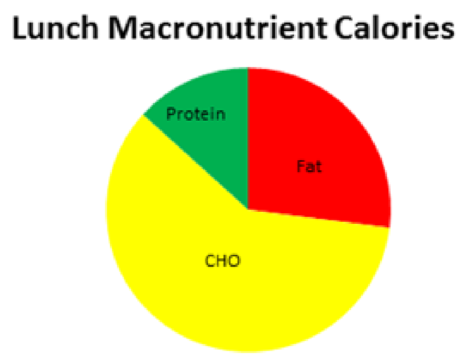


**Figure 6:** Macronutrient composition of Ms. X's optimal meal.

## Mi Volumetrics versus the "Old ways"

Finally, it may be instructive to compare the Mi Volumetrics approach to the traditional way of meal planning. To do that, we can compare Ms. "X"—our sophisticated user of Mi Model and Mi Volumetrics—to a Ms. "Old-ways," a comparable dieter who also starts at the same weight (75 kg) and base-line diet (2,500 kcal) and who has also decided to go on a diet to lose weight. We'll also assume that her satiated threshold is similar to Ms. "X" (600 g for lunch). And (again, just like Ms. "X"), her base-line (pre-diet) satiating lunch is a 900 kcal lunch and at 600 g yields an average energy density of 1.5 kcal/g.

That's where the similarities between the two dieters end. Moving forward, Ms. "Old ways" approaches her weight-loss effort in manner that's very different from that of Ms. "X":

- Rather than picking a realistic goal, she goes for her "dream" goal (as many dieters tend to do) [16]: To lose 10 kg (equivalent to 22 pounds) in 3 months.
- Rather than using Mi Model, she relies on the energy balance equation (the 3,500 kcal per pound rule). Her calculus, thus, proceeds as follows:

| Food | Bread, pita, white | Hummus | Mushroom soup, condensed, canned, prepared with 2 percent | Lettuce, romaine | Potatoes, French-fried | Chicken breast, roasted, no skin | Pickles dill | Wine, red | Banana |
|---|---|---|---|---|---|---|---|---|---|
| **E.D** | 2.75 | 1.77 | 0.79 | 0.17 | 3.33 | 1.65 | 0.18 | 0.85 | 0.89 |
| **Calories (per serving)** | 162.25 | 218.6 | 199.87 | 8.5 | 93.24 | 135.8 | 10.8 | 103.19 | 107.69 |
| **Weight** | 59 | 123.5 | 253 | 50 | 28 | 82.3 | 60 | 121.4 | 121 |
| **Fat (g)** | 0.71 | 10.61 | 13.41 | 0.15 | 5.24 | 3.29 | 0.11 | 0 | 0.4 |
| **Carbohydrates** | 32.86 | 24.85 | 17.2 | 1.65 | 11.11 | 0 | 2.48 | 3.17 | 27.64 |
| **Protein** | 5.37 | 6 | 3.42 | 0.62 | 0.99 | 25.51 | 0.37 | 0.08 | 1.32 |
| **Fiber** | 1.3 | 4.94 | 1.77 | 1.05 | 0.9 | 0 | 0.72 | 0 | 3.15 |
| **L Foods Used** | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| **L Servings** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **L Calories Served** | 162.3 | 218.6 | 199.9 | 8.5 | 93.2 | 135.8 | 10.8 | 103.2 | 107.7 |
| **L Weight Served** | 59 | 123.5 | 253 | 50 | 28 | 82.3 | 60 | 121.4 | 121 |
| **L Fat Served (g)** | 0.7 | 10.6 | 13.4 | 0.2 | 5.2 | 3.3 | 0.1 | 0 | 0.4 |
| **L CHO Served (g)** | 32.9 | 24.8 | 17.2 | 1.6 | 11.1 | 0 | 2.5 | 3.2 | 27.6 |
| **L pr Served (g)** | 5.4 | 6 | 3.4 | 0.6 | 1 | 25.5 | 0.4 | 0.1 | 1.3 |
| **L Fbr Served (g)** | 1.3 | 4.9 | 1.8 | 1.1 | 0.9 | 0 | 0.7 | 0 | 3.1 |
| **L Must-Haves** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 5:** Optimization model input.

| Proposed Lunch Entries | Servings |
|---|---|
| Cream of mushroom condensed, canned, prepared soup with 2 percent milk | 1 |
| Lettuce, romaine | 1 |
| Chili, vegetarian with three beans | 1 |
| Pickles, dill | 1 |
| Wine, red | 1 |
| orange | 1 |
| 569 | Calories |
| 836 | Wt (g) |
| Lunch Weight (g): 836 | |
| Lunch Calories: 569 | |

**Table 6:** Optimal meal.

- 22 pounds are worth: 22×3,500 = 77,000 kcal.
- 77,000 kcal deficit over 3 months (90 days) translates to 77,000/90 = 855 kcal/day.
- This means she needs to reduce her daily caloric intake from 2,500 kcal to 2500–855 = 1,645 kcal.
- Using the same meal allocations as Ms. "X," her lunch's caloric content = 0.3×1,645 = 493 kcal.

- Rather than using Mi Volumetrics to compose an optimal lunch, we'll assume she uses the common (though naïve) strategy of simply eating smaller portions of the foods she is currently eating. This means that while her lunch's bulk will decrease, the meal's energy density (of 1.5 kcal/g) stays the same. From this we can calculate that her 493 kcal lunch will weigh approximately 330 g.

The Table 7 below compares the two dieters' situations.

The striking differences between the two meal plans are nicely manifested when plotted on Mi EDPP. As Figure 7 clearly indicates, Ms. "X" is meeting her caloric target and does so on a meal plan that does not leave her feeling hungry and deprived her optimal meal falls outside the 600 g "hungry circle." Ms. "Old ways" lunch, on the other hand, falls within the hungry circle (because it is below the 600 g threshold) leaving her feeling hungry and deprived. Which doesn't bode well for her long-term prospects. In all likelihood, she'll just wind up hungry and unhappy and most probably will go back to her old ways.

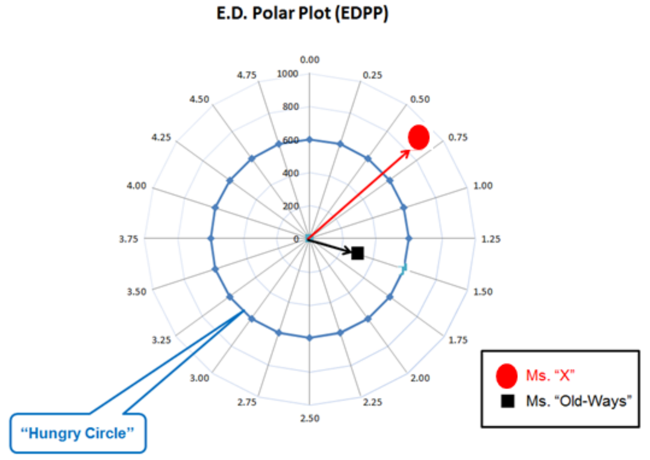


**Figure 7:** Comparison of two dieting strategies.

| | Ms. "X" | Ms. "Old-ways" |
|---|---|---|
| Current weight | 75 kg (BMI:33) | 75 kg (BMI:33) |
| Current SS Daily Food Intake | 2,500 kcal | 2,500 kcal |
| Current Lunch | 900 kcal, 600 g | 900 kcal, 600 g |
| Weight-Loss target | 5.5 kg in 3 months | 10 kg in 3 months |
| Diet Caloric Intake | 2,000 kcal (Lunch: 600 kcal) | 1,645 kcal (Lunch: 493 kcal) |
| Lunch (optimal) | 600 kcal, 836 g | 493 kcal, 330 g |

**Table 7:** Comparison of dieters.

## "Give us the Tools and we'll finish the Job" - Churchill

While computer-supported optimization continues to make impressive inroads in business, public policy, and the military their use in personal health management remains limited however. This needs to change and slowly is changing. Few would disagree that health is precisely the setting where sub-optimality is the most problematic and where the stakes are the highest. As we start assuming more responsibility for managing our health, the ability to understand and (effectively use) optimization models will (I believe) fast become a prerequisite for effectively managing our well-being.

It seems paradoxical, but the wondrous advances in health care over the last century a period historians hail as the time of the "great flowering of medicine" have made the task of managing personal health more critical and complex not less. Improved medical care and the elimination of infectious diseases have increased life expectancy so that minor dysfunctions due to personal mismanagement have now more time to morph into chronic ailments later in life. A good (bad?) example of the challenges and the mismanagement is the growing obesity problem. A century ago, when the life expectancy was only 40, gaining 30 or 40 pounds at the age of 20 or 30 would not have been too much of a concern. A century later, the life expectancy of the United States population has nearly doubled, from 40 to almost 80 years (although the trend may be reversing), which means that there is ample time for those 30 or 40 pounds to translate into serious ailments (including hypertension, heart disease, type 2 diabetes, even cancer) [17].

Today, what we desperately need is a "second great flowering" in personal health management, one that promotes the customization of healthcare and where medicine seeks not just to cure disease but to develop our capacities to prevent it. The ticket, many in public health increasingly believe, is the growing and synergistic entwinement of the healing and personal digital technologies.

An expanding repertoire of personal information technologies is engendering enormous possibilities for empowering ordinary people with the learning and decision-making tools they need to better manage personal health and wellbeing. Particularly exciting is how easily (and economically) these new generation etools can be tailored to each person's health needs, lifestyle (why they do or do not do), and even style of thinking.

Mi Volumetrics ---a decision-support tool to help lay dieters customize meal planning ---is such a tool.

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