

Data Mining inspired Sensory Mapping Algorithm.

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- Existing methodologies cannot accurately establish the complex relationship between analytical measurements, consumer sensory responses and purchase intent.
- This is mainly due to their inability to model the interdependence between the pertinent variables.
- Consequently, product developers and marketing practitioners are still searching for the “best” course that is likely to enhance product acceptance/sales.
- Sensory Mapping Algorithm exploits the versatile Structural Equation Modeling (SEM), a methodology that combines the properties of casual econometrics models with factorial analysis.

The algorithm is guided by the following assumptions

1. Customers' response is subjected to measurement errors.
2. Physicochemical variables are affecting sensory attributes either directly or via a latent variable, depicting an unobserved interaction between some of the physicochemical and sensory variables.
3. Sensory attributes possess errors in their measurements, an error that manifests the variability in the subjective assessment of the respondents.
4. Sensory attributes may be interrelated.
5. Degree of acceptance (or purchase intent) is not affected by physicochemical concentration directly, but through the sensory attributes.

Sensomatrix™

Dialog boxes

Sensomatrix Application

Sensomatrix™

Model Matrix

	Bx_chem	Sour_chem	Pulpa_chem	SO2_chem	SweetT	SourT	OrangeT	PulpaT	aroma1	after1
Bx_chem	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
Sour_chem	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
Pulpa_chem	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
SO2_chem	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
SweetT	↖weight	↖weight	↖weight	↖weight	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
SourT	↖weight	↖weight	↖weight	↖weight	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
OrangeT	↖weight	↖weight	↖weight	↖weight	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
PulpaT	↖weight	↖weight	↖weight	↖weight	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath
aroma1	↖weight	↖weight	↖weight	↖weight	NoPath	NoPath	NoPath	NoPath	NoPath	NoPath

Model: Fixed weights, Allowed Path

Model Equations:

```

Bx_chem=(1)↖Bx_chem
Sour_chem=(1)↖Sour_chem
Pulpa_chem=(1)↖Pulpa_chem
SO2_chem=(1)↖SO2_chem
SweetT=(1)↖Bx_chem+Sour_chem
Pulpa_chem+SO2_chem=(1)↖SweetT
SourT=(1)↖Bx_chem+Sour_chem
Pulpa_chem+SO2_chem=(1)↖SourT
OrangeT=(1)↖Bx_chem+Sour_chem+
Pulpa_chem+SO2_chem=(1)
    
```

Estimation Criterion: ML

Extra Parameters: Method: 2, Remove: 1, Stepwise: True

Prediction Values:

Bx_chem	Sour_chem	Pulpa_chem	SO2_chem	SweetT	SourT	OrangeT
11.4	0.41	29	28			

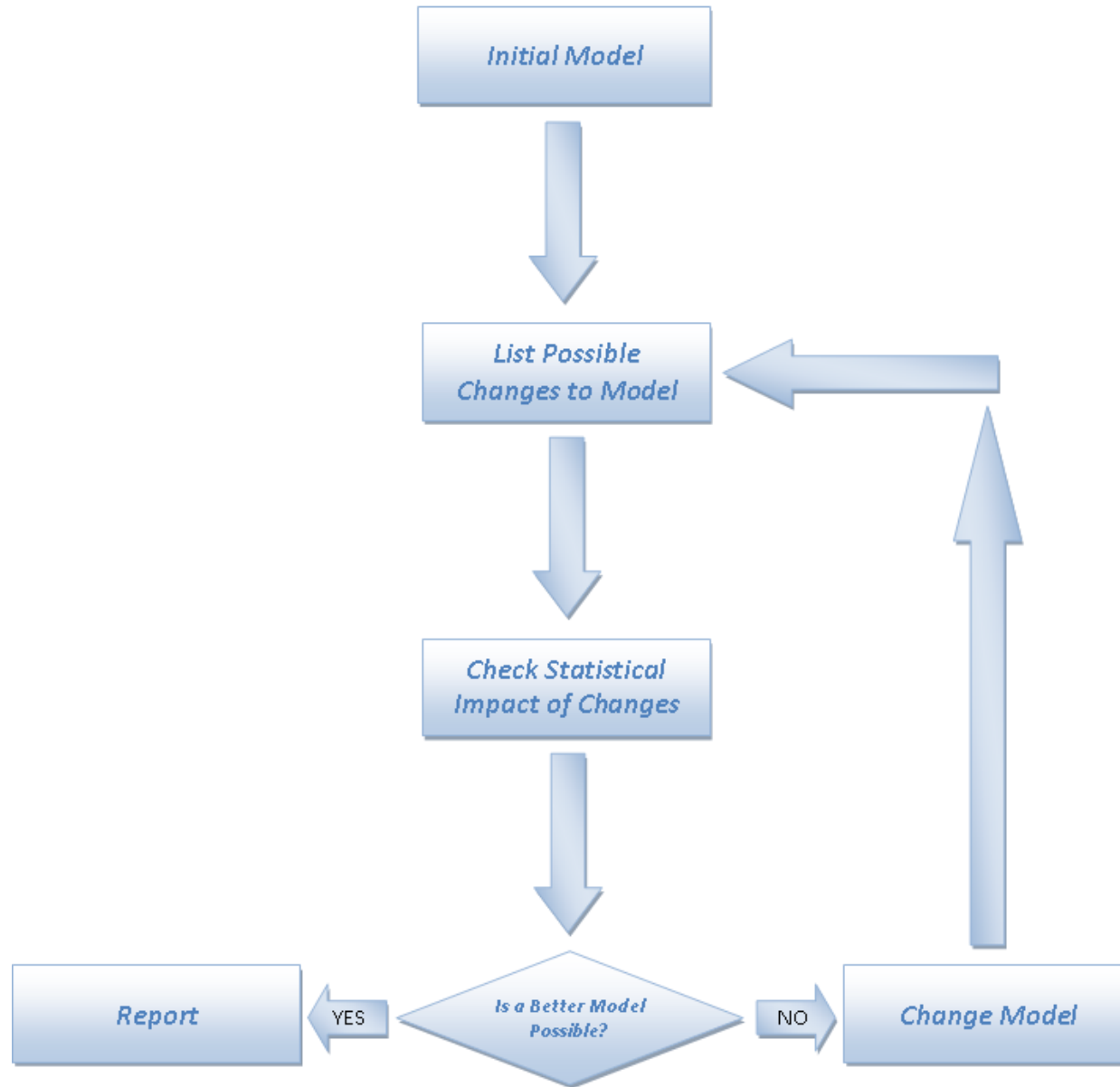
Shake: 0.0000000, k: 70

Estimate by Lab. only, Correct Estimation if StDev above: 3

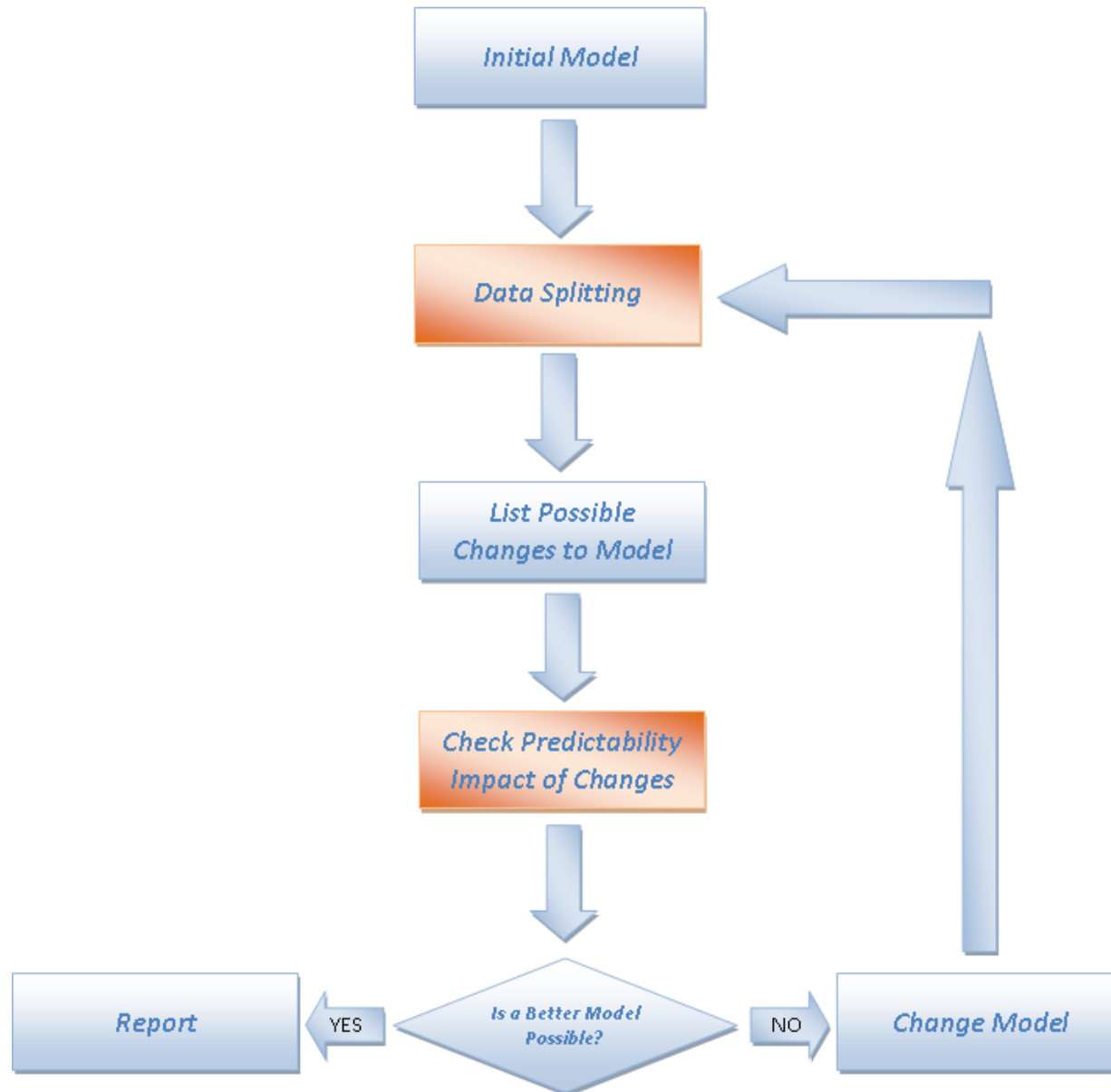
Sig. Threshold (alpha): 0.05

Buttons: Phase 1, Phase 2, Report

Flowchart of Sensomatrix[®] – Phase I



Flowchart of Sensomatrix[®] – Phase II



The SMA comprises of four phases

1. **The technological phase**, relating physicochemical values to sensory attributes.
2. **The sensory phase**, relating sensory attributes to purchase intent.
3. **The prediction phase**, predicting purchase intent of an R&D product using a suggested physicochemical profile.
4. **The validation phase**, assessing the validity of the model and its predictive power.

Numerical study

Aim:

To develop a model for predicting purchase intent for orange drinks by linking product physicochemical data (e.g., solids content, pH, acidity, SO₂, pulp concentration) with sensory evaluations; and to verify model accuracy for predicting purchase intent.

Table 1: Average analytical properties

Beverage	°Bx	Acidity (%)	Pulp	SO₂ (ppm)
A	11.20	0.42	34.00	21.00
B	11.50	0.52	35.00	27.00
C	11.20	0.42	32.50	25.00
D	11.20	0.42	47.50	0.00
E	10.90	0.42	50.00	68.00
F	10.60	0.41	20.00	64.00
G	11.00	0.47	29.00	21.00
H	11.10	0.52	32.00	19.00
I	11.20	0.45	35.00	16.00
J	11.30	0.40	0.00	0.00
K	11.30	0.40	40.00	0.00
L	11.00	0.42	50.00	61.00

Table 2: Average sensory evaluation and purchase intent (0 - lowest to 99 - highest)

Orange drink	Sweetness	Sourness	Fruit flavor	Pulpiness	Overall aroma	After-taste	Purchase intent
A	88.4	91.5	87.2	85.8	66.3	2.8	72.5
B	88.1	91.5	86.4	85.1	67.8	3.0	73.0
C	88.2	89.0	86.7	85.7	69.4	2.8	71.6
D	88.8	91.0	89.2	86.1	75.4	3.7	78.6
E	87.8	87.1	87.4	88.1	74.8	3.6	75.3
F	88.3	89.4	86.4	85.3	68.7	4.9	69.7
G	88.1	88.0	85.4	84.9	68.4	3.1	75.1
H	88.2	90.0	85.9	85.2	66.7	3.0	74.0
I	88.5	90.3	86.9	86.5	69.2	2.7	74.0
J	89.9	90.1	90.7	89.3	76.6	2.5	77.6
K	88.6	93.0	90.6	87.7	75.2	1.8	79.6
L	88.4	91.3	89.0	84.4	71.6	2.5	75.1

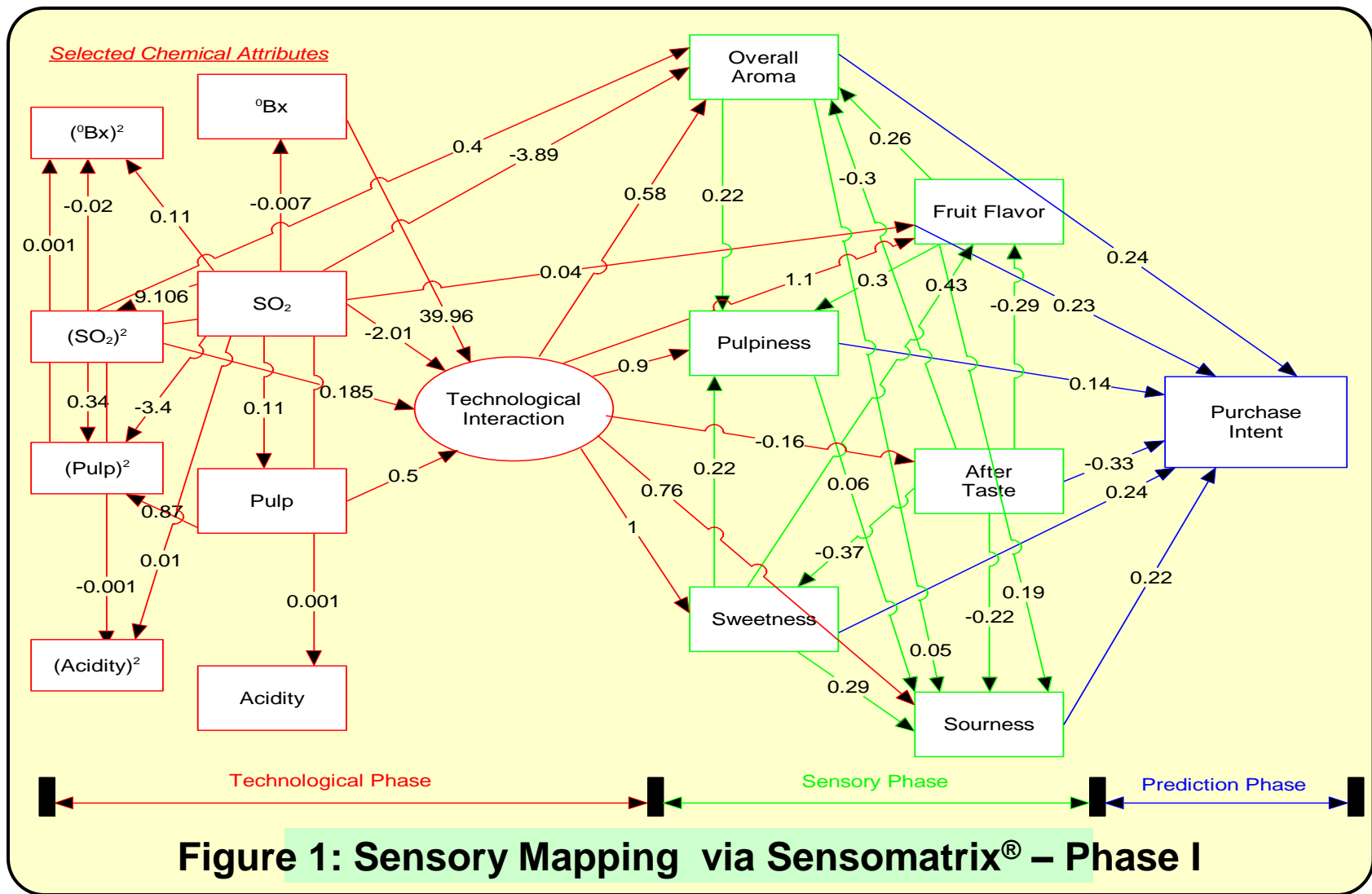


Figure 1: Sensory Mapping via Sensomatrix® – Phase I

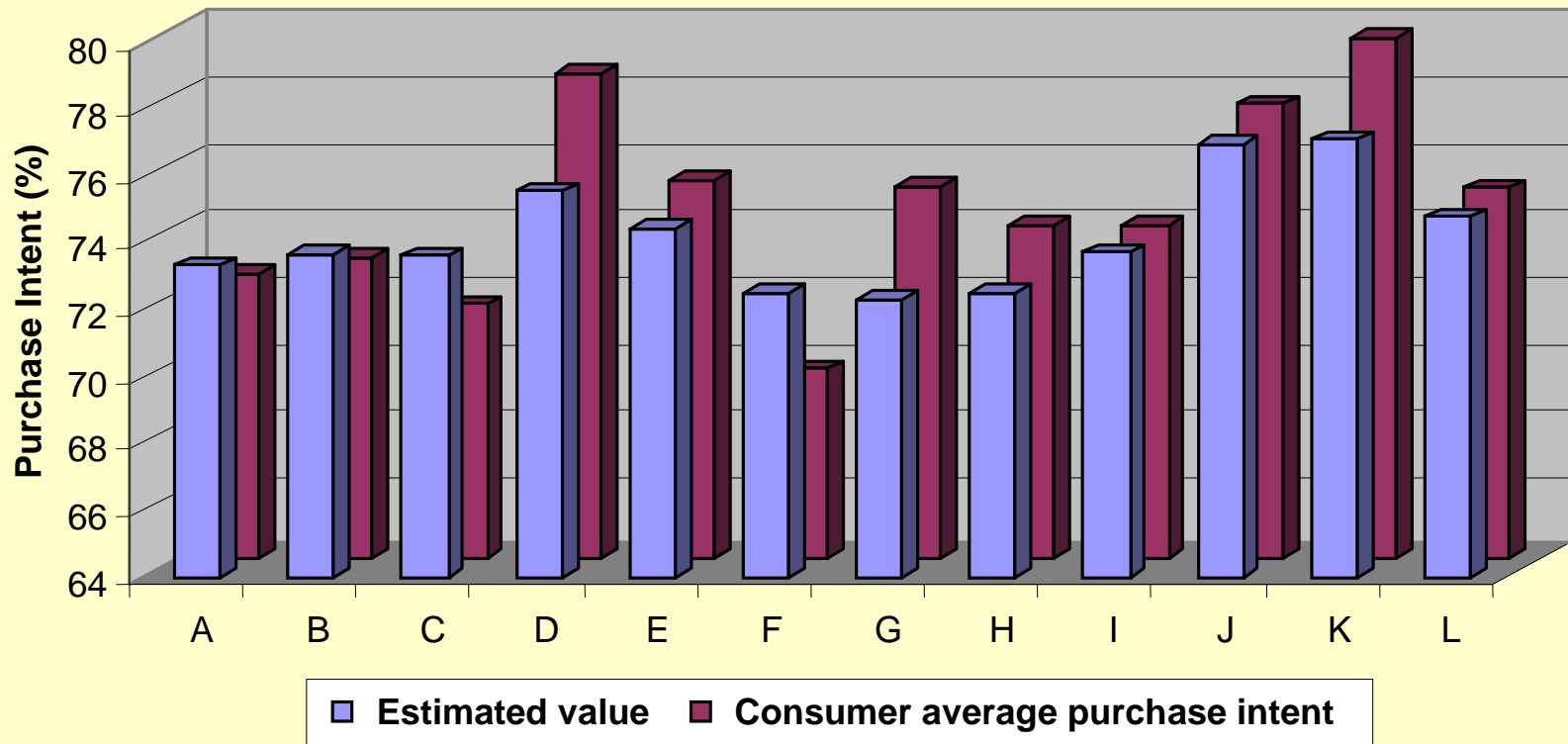


Figure 2: Actual and estimated purchase intent

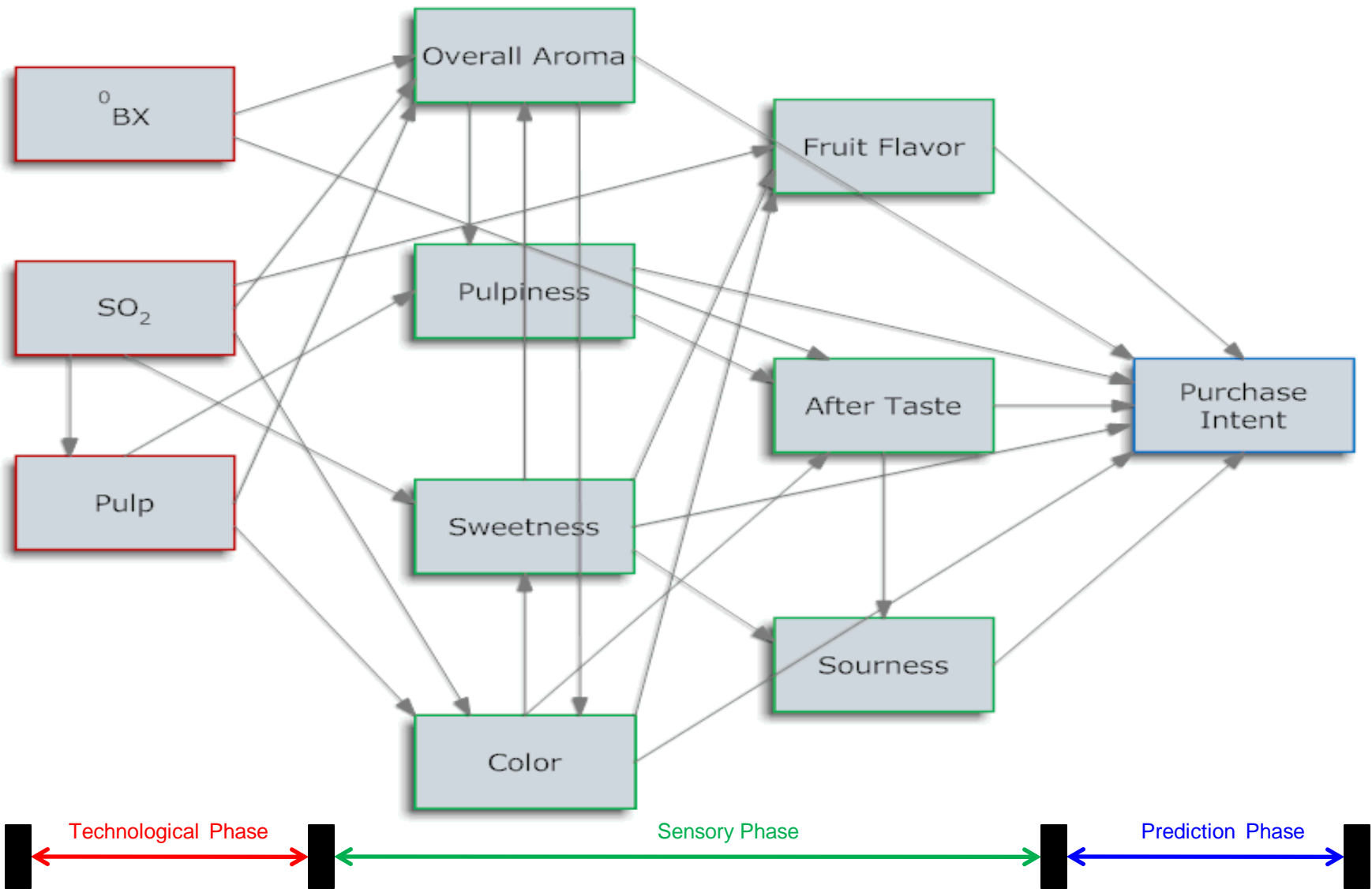


Figure 3: Sensory Mapping via Sensomatrix® – Phase II

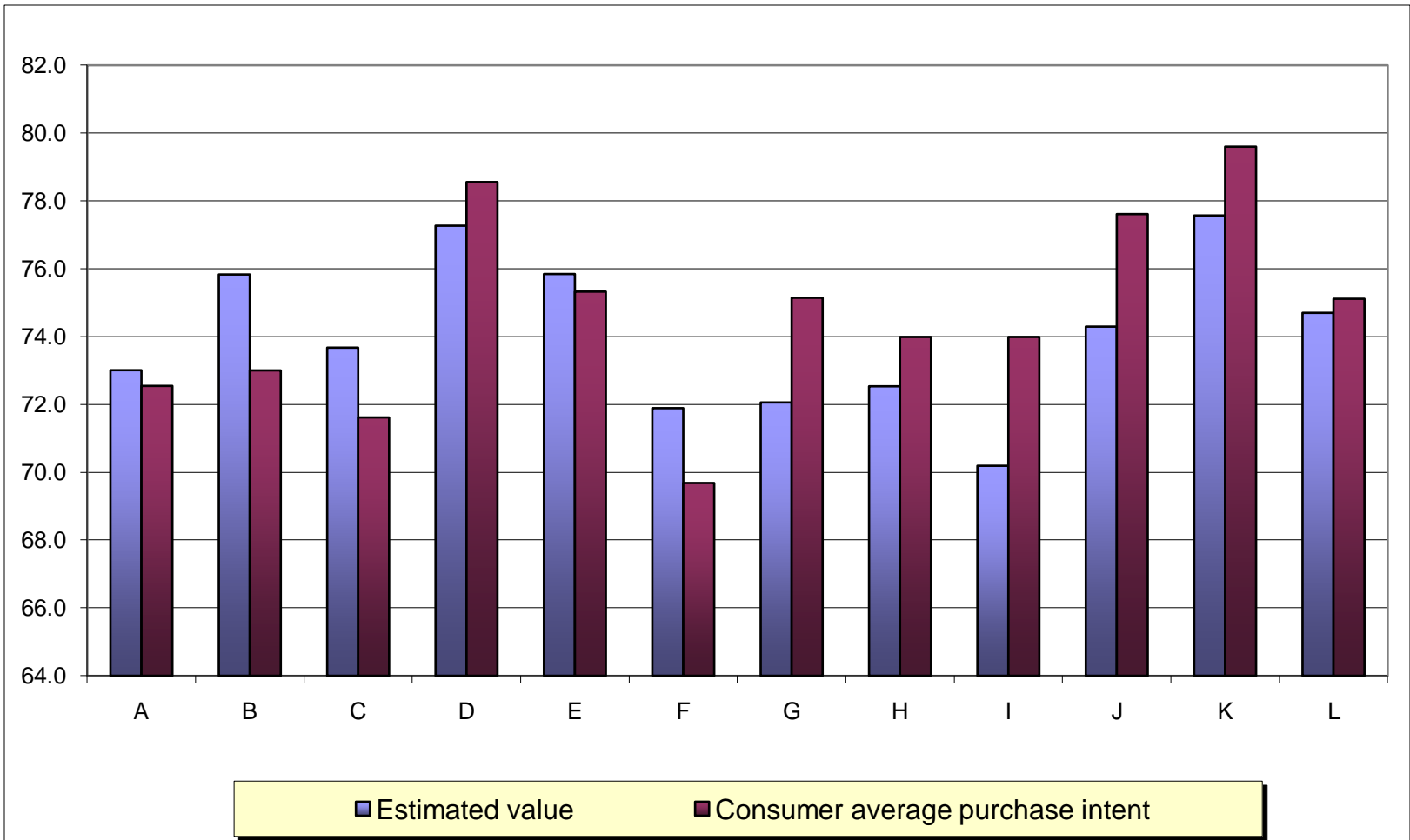


Figure 4: Actual and Estimated Purchase Intent

Conclusions

- The results demonstrated that the model could successfully relate analytical data (physicochemical composition and physical properties) with sensory evaluations and consumers' purchase intent.
- The model is also able to predict, quite accurately, consumer's response and purchase intent of a product for which only a laboratory profile is available.
- Once the parameters of the model are derived, the assessment of the direction the product development practitioner should follow can be based entirely on the model prediction, circumventing the need for extensive and expensive improvements steps, and sensory consumers' studies.
- The model could be used to significantly shorten product development and increase its overall chance to compete successfully in the marketplace.