Service Intelligence Week 6.

[Learning Behavioral Data of Customers for Personal Process Management]

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2022. 10. 5

Today's Topic in the Framework of This Course

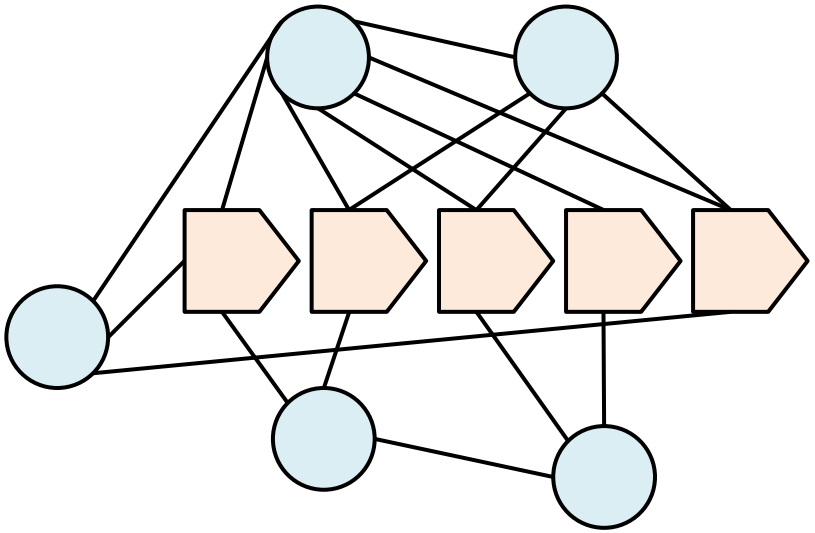
consumer behaviors
(user behaviors)

service delivery
and experience

quality

value cocreation

technology and
self-service



relationship

innovation

design and
development

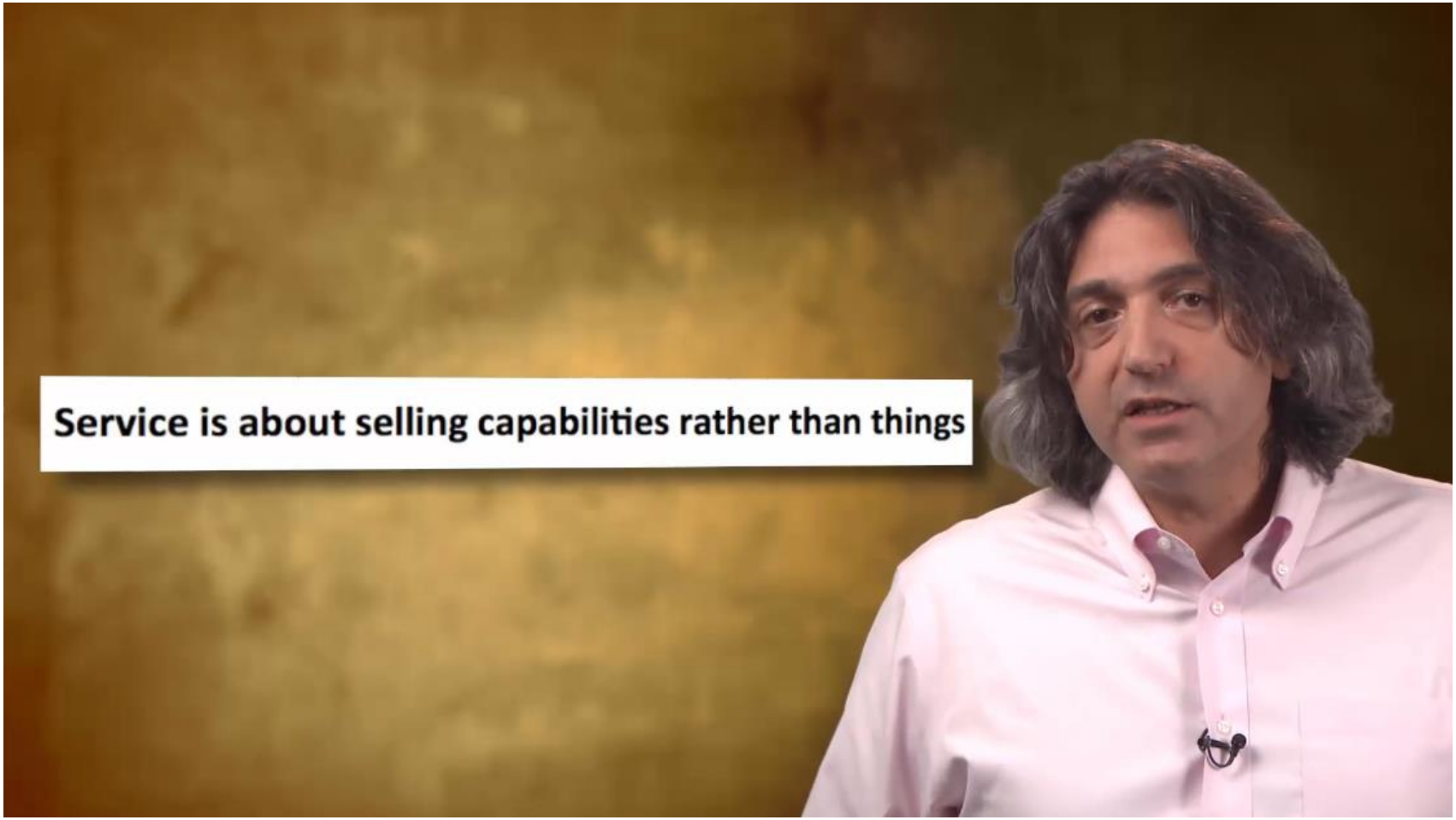
productivity

knowledge and
employee
management

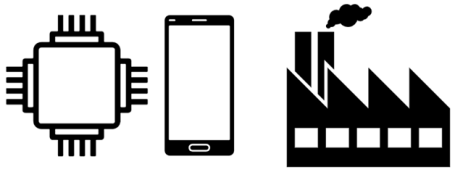
cost and pricing

service operations
and supply chain
management

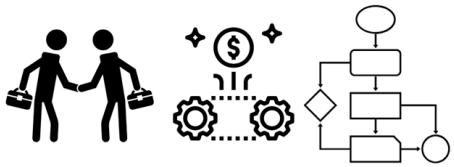
Service is Simply to Serve Customers: Help Tasks or to Do the Tasks



Tasks in Industry and Society: A Process Viewpoint



Manufacturing Process

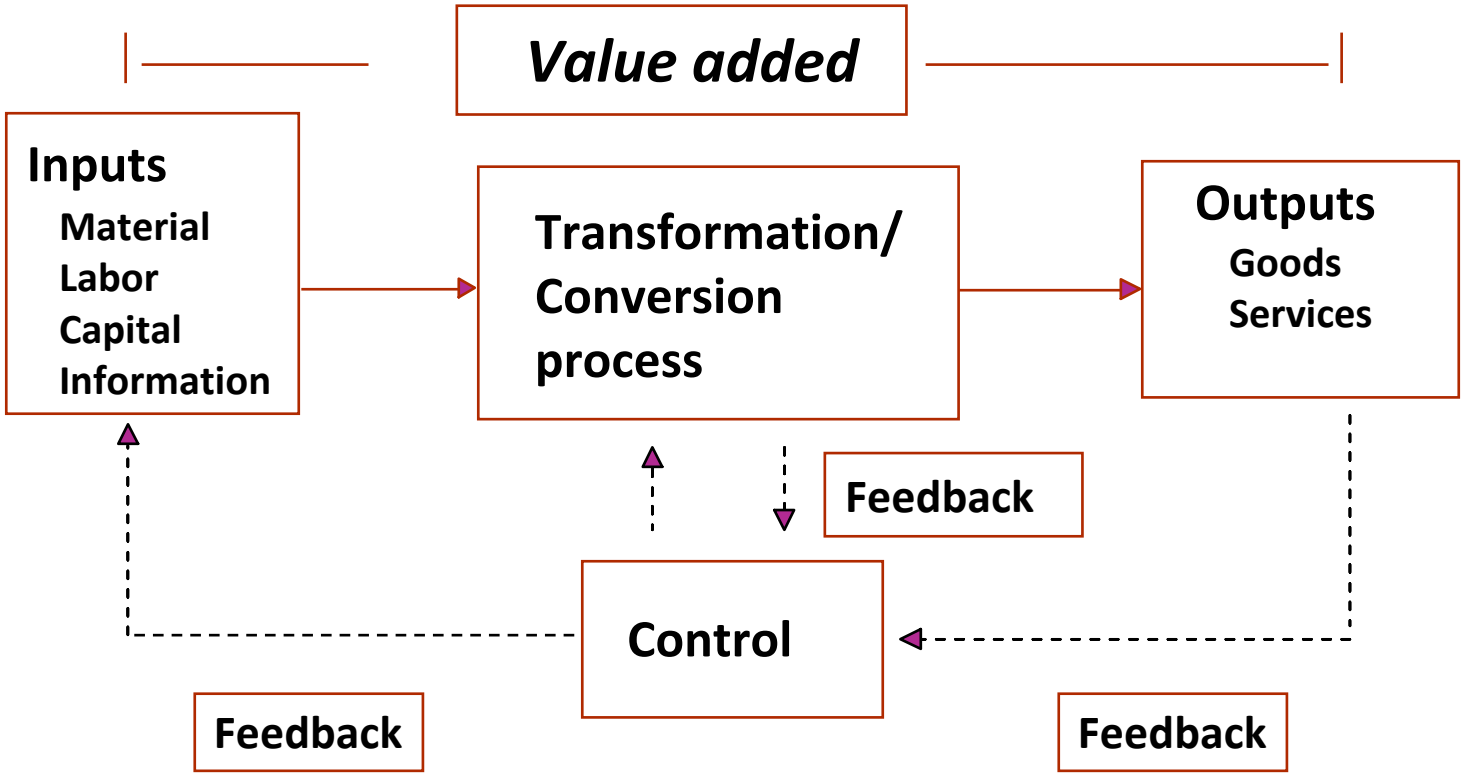


Business Process

Personal Process

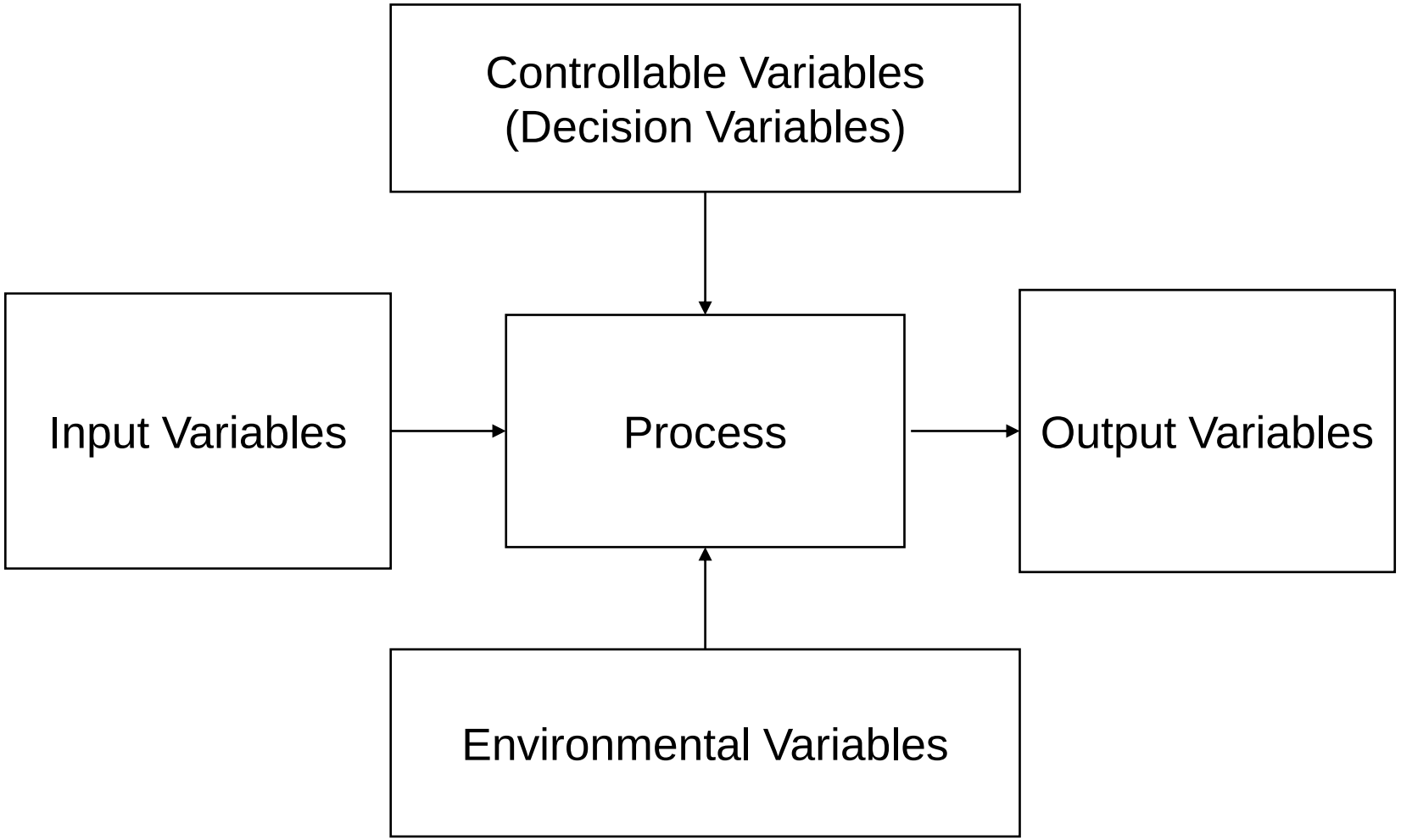
Definition of Process

- A process involves the conversion of inputs into outputs

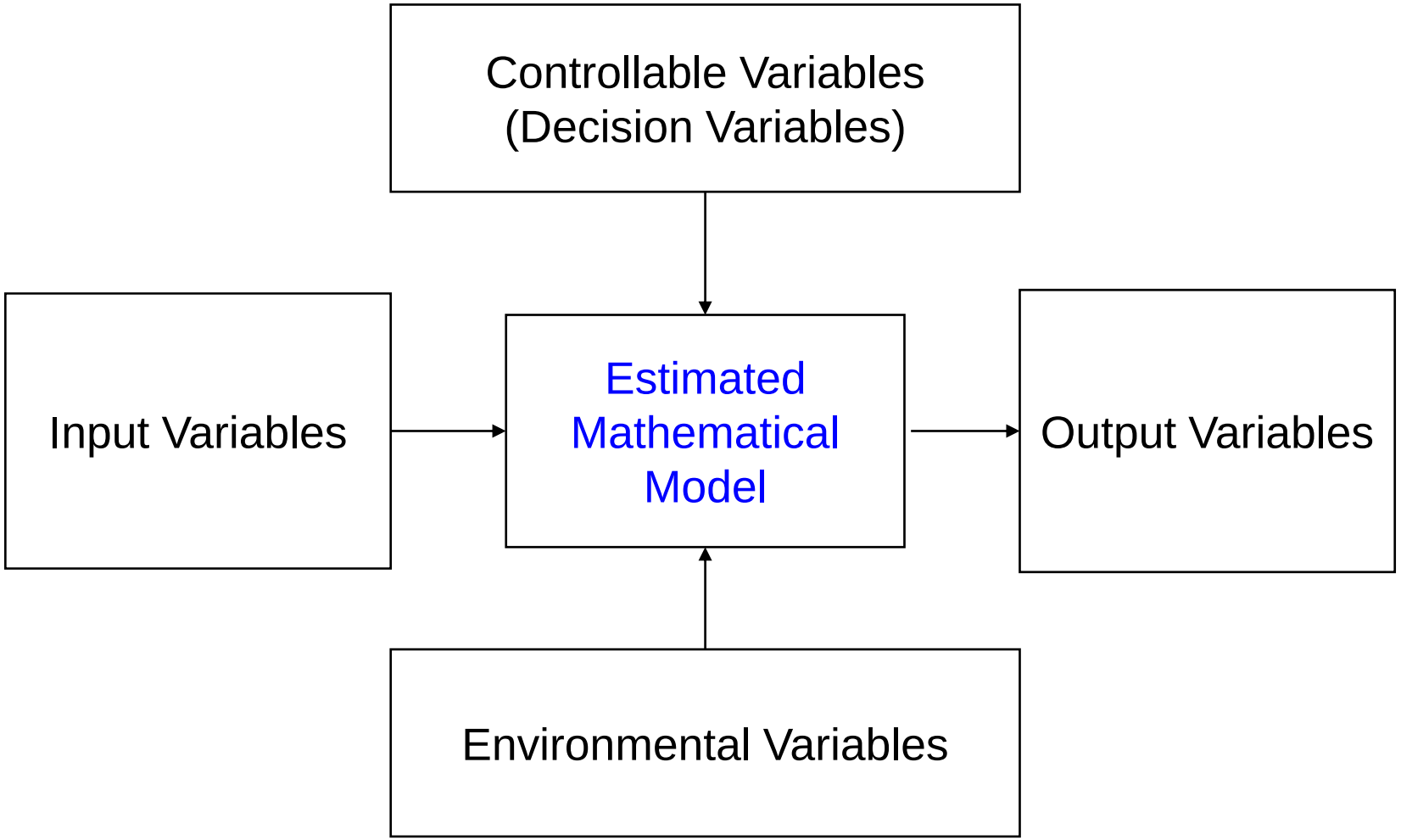


Reference: Stevenson and Chuong, *Operations Management* (2nd edition), McGraw-Hill.

Conceptual Framework of Process Management



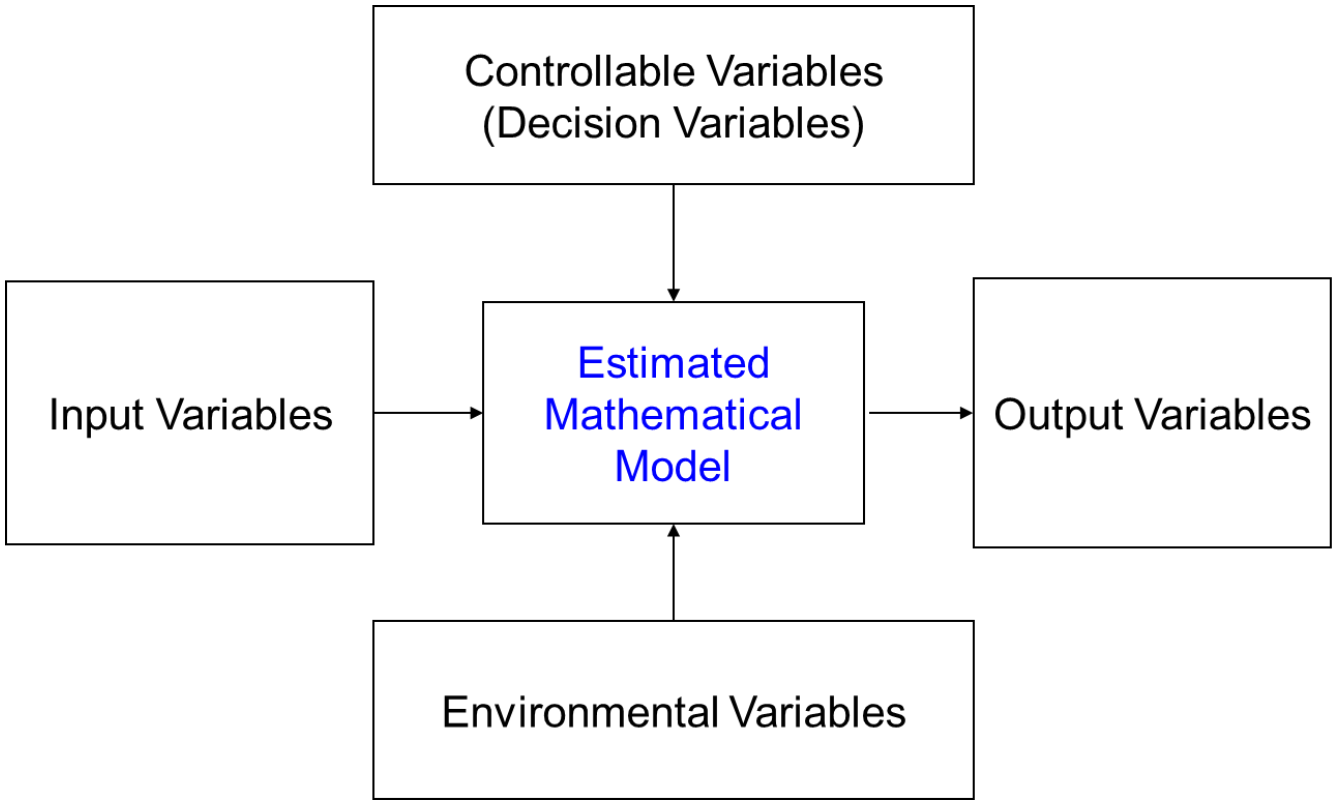
Conceptual Framework of Data-driven Process Management



Conceptual Framework of Data-driven Process Management

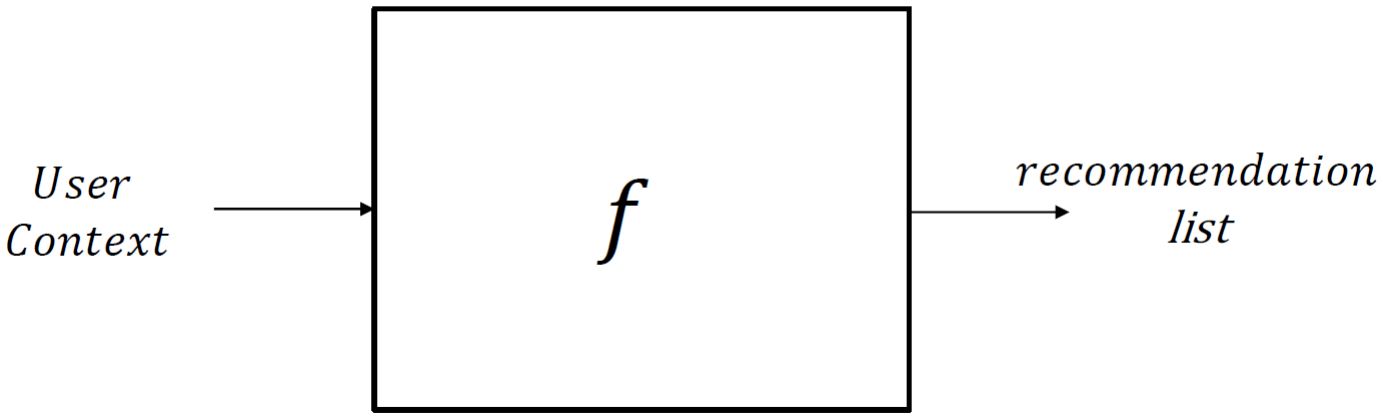
"Model building" "Search optimal setting for **x**"

$$y = f(\mathbf{x}, \boldsymbol{\theta}) + \varepsilon \quad \rightarrow \quad \hat{y}(\mathbf{x}) \quad \rightarrow \quad \underset{\mathbf{x} \in \Omega}{\text{optimize}} \ \hat{y}(\mathbf{x})$$

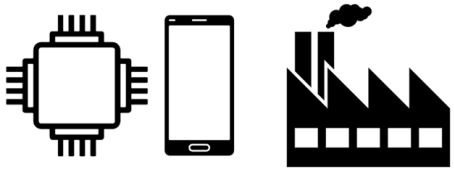


Relation to a Previous Framework We Discussed

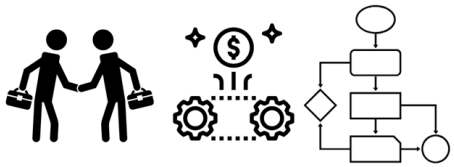
$$y = f(x)$$



Process Management (Services) in Industry and Society



Manufacturing Process Management



Business Process Management

Personal Process Management

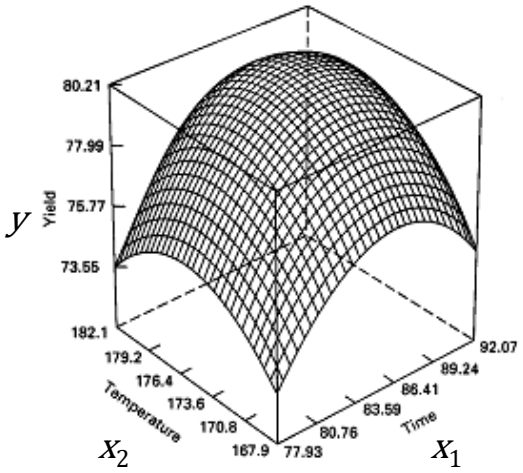
An Example of Manufacturing Process Management

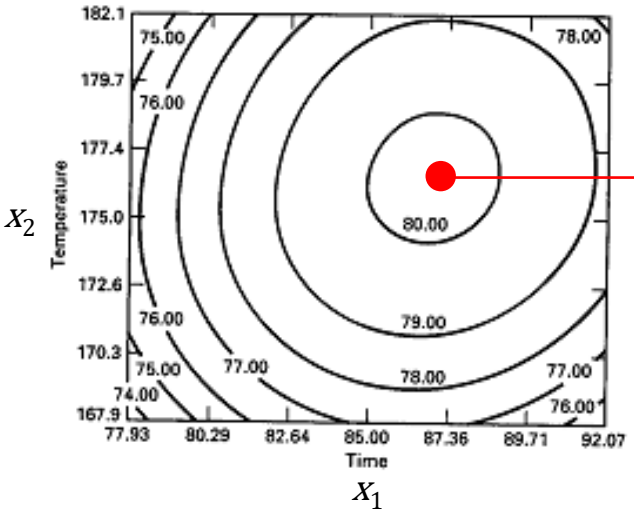
"Model building" "Search optimal setting for **x**"

$$y = f(\mathbf{x}, \boldsymbol{\theta}) + \varepsilon \rightarrow \hat{y}(\mathbf{x}) \rightarrow \underset{\mathbf{x} \in \Omega}{\text{optimize}}\ \hat{y}(\mathbf{x})$$

Example*

y = process yield (Larger the better),
x_1 = reaction time, x_2 = reaction temperature



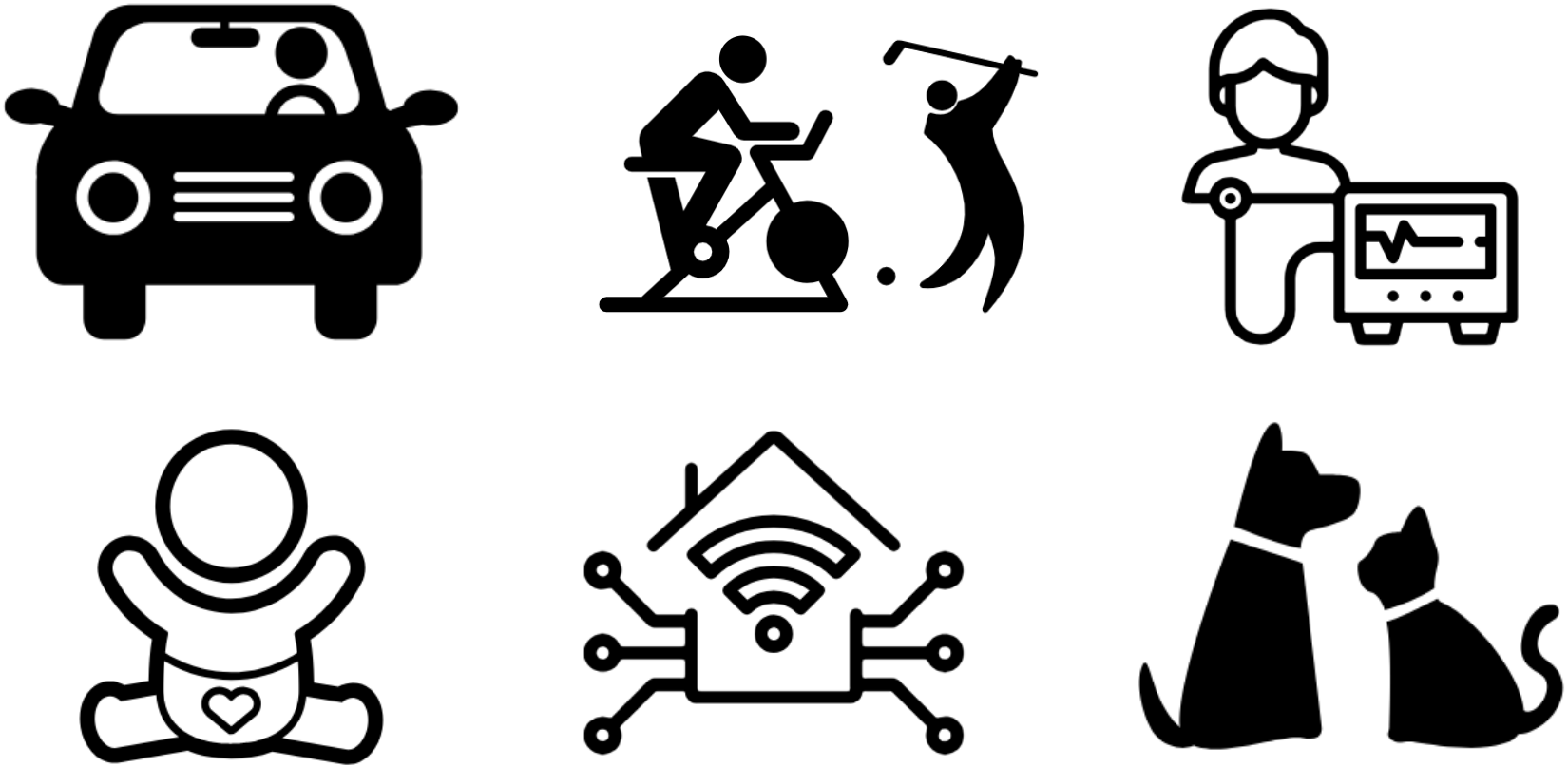


$\hat{y}_1^* = 80.21$ at $\mathbf{x}^* = (87.0, 176.5)$

Source: Response Surface Methodology (Myers and Montgomery, 1995)

Emergence of Personal Process Management

- Data from people and objects with which they interact



Service is Simply to Serve Customers: Help Tasks or to Do the Tasks

- Data are collected in a connected network of objects and people
- Data contribute to monitoring the concerned objects and people, evaluating the status and condition, and identifying what tasks should be supported for the customers in which way
- A.I. solutions contribute to automate and/or improve specific tasks involved in the service

Volvo Trucks:
Telematics Gateway

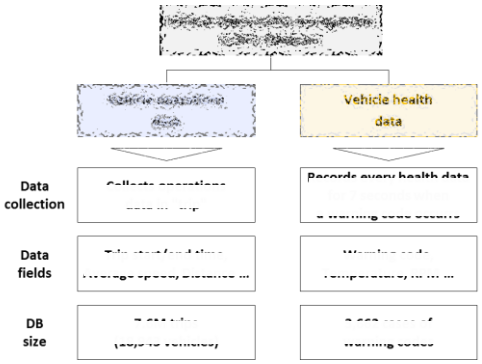
BMW:
ConnectedDrive

IBM:
Precision Agriculture

More cases with
consumer electronics

Reference: Design of informatics-based services in manufacturing industries (Lim et al., 2015)

An Example of Personal Process Management



Data related to driving processes

Driving process

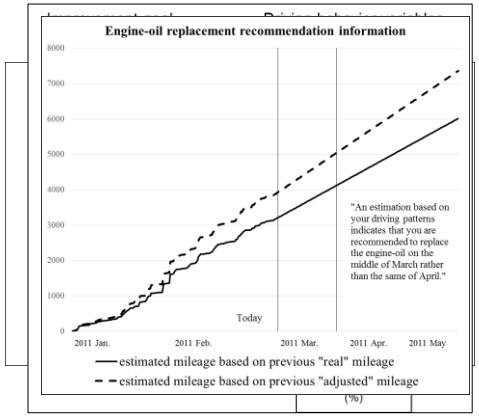
Service for driving process management

Continuous process improvement

Driving characteristics (annual)	Driver 1	Driver 2	...	Driver 1688
Number of trip	874	382	...	87
Mileage (km)	6656	2276	...	872
Average mileage per trip (km)	7.62	5.96	...	10.02
Ratio of short trip (< 18km)	91.08	97.64	...	87.36
Average of low speed (< 29 km/h) ratio per trip	73.18	72.87	...	68.15
Engine oil deterioration indicator 1	284	159	...	34
Engine oil deterioration indicator 2	32.49	41.62	...	39.08
Tire wear indicator 1	0.018	0.018	...	0.019
...	...	...	...	...

Driving process characteristics

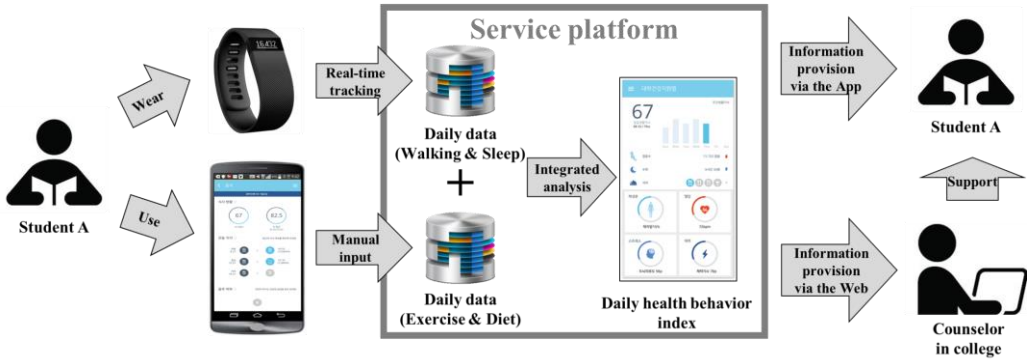
Driving process analysis

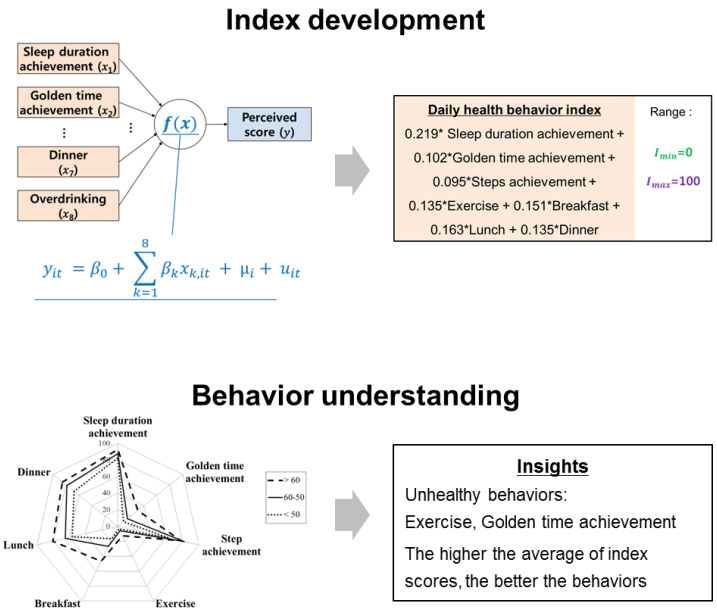


Information for process improvement

Reference: “Customer Process Management” (Lim et al., 2019; *JoSM*)

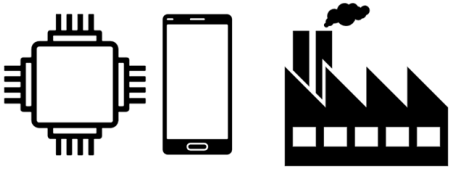
An Example of Personal Process Management





Source: Kim, K., Kim, K., Lim, C., and Heo, J., "Development of a Lifelogs-based Daily Wellness Score to Advance a Smart Wellness Service," *Service Science*, Vol. 10, No. 4, 408–422, 2018.

What is the Difference?

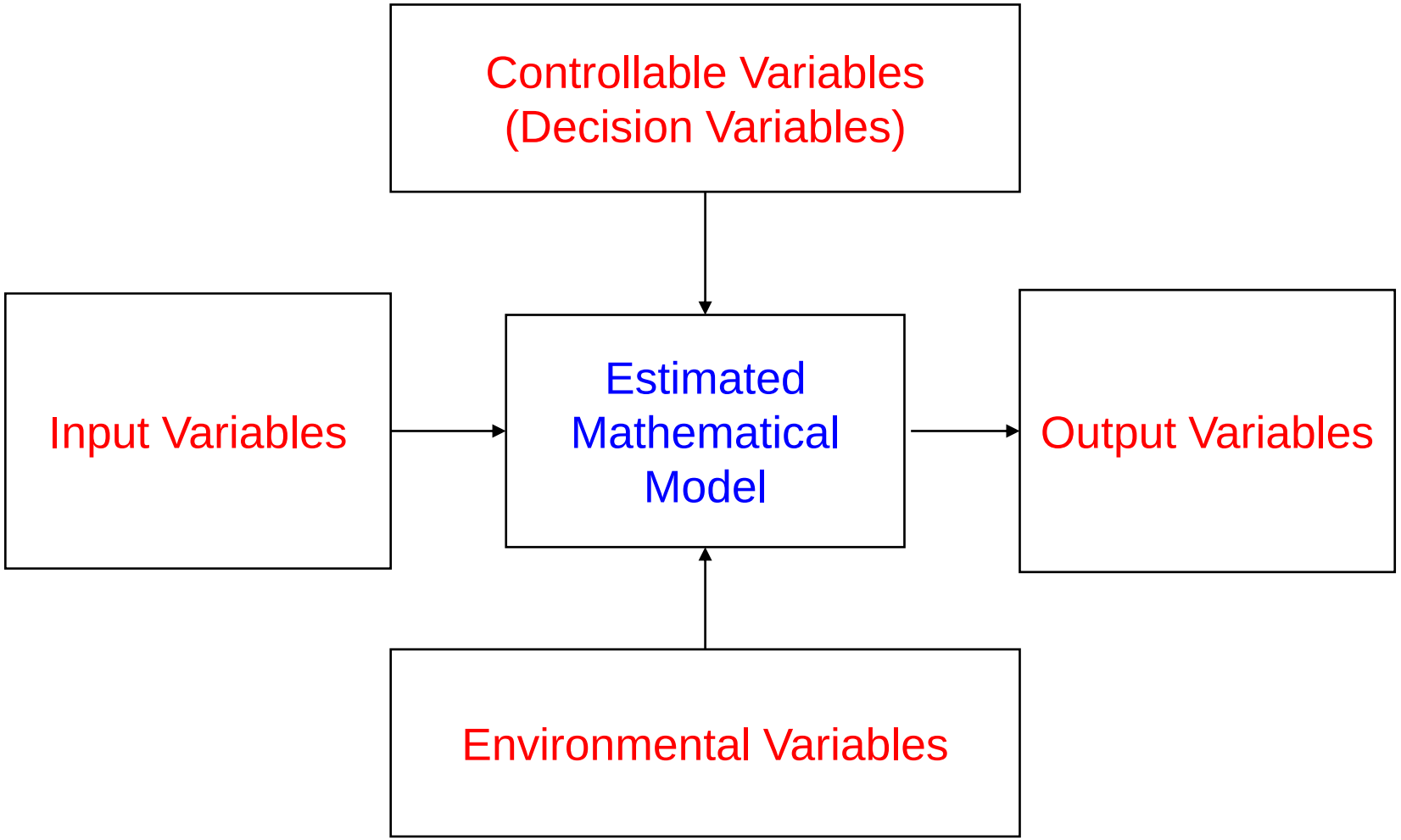


Manufacturing Process Management

vs.

Personal Process Management

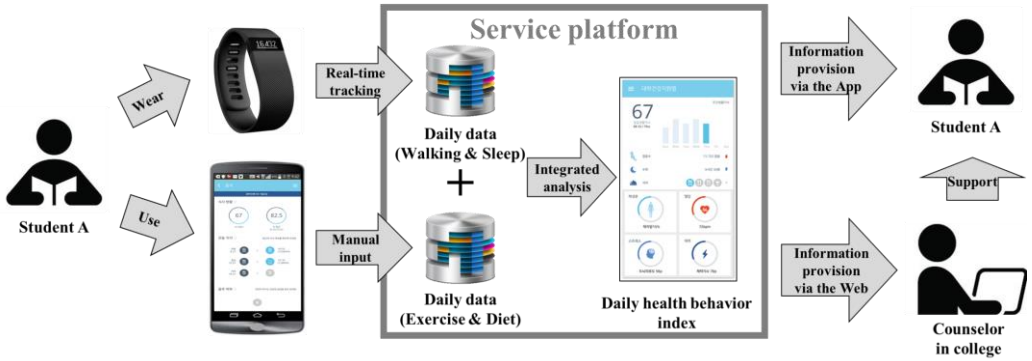
Conceptual Framework of Data-driven Process Management

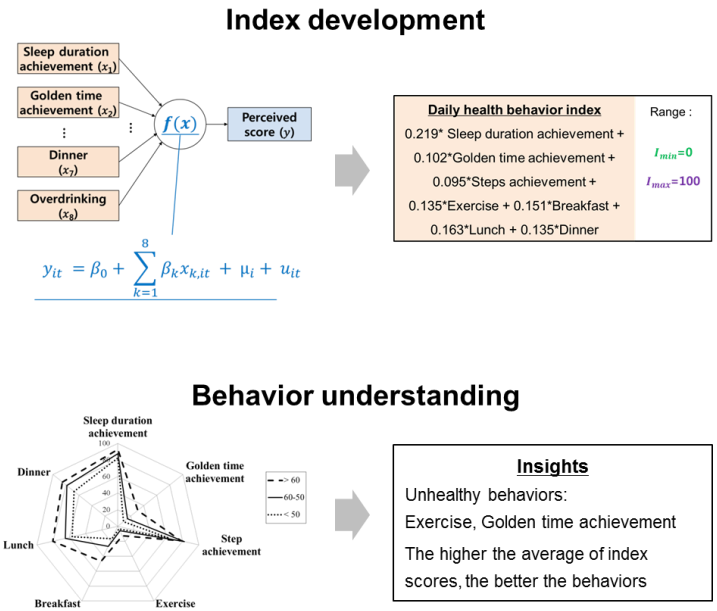


Personal Process Management:

in the Context of Healthcare Task Support

Personal Process Management in the Context of Healthcare Support



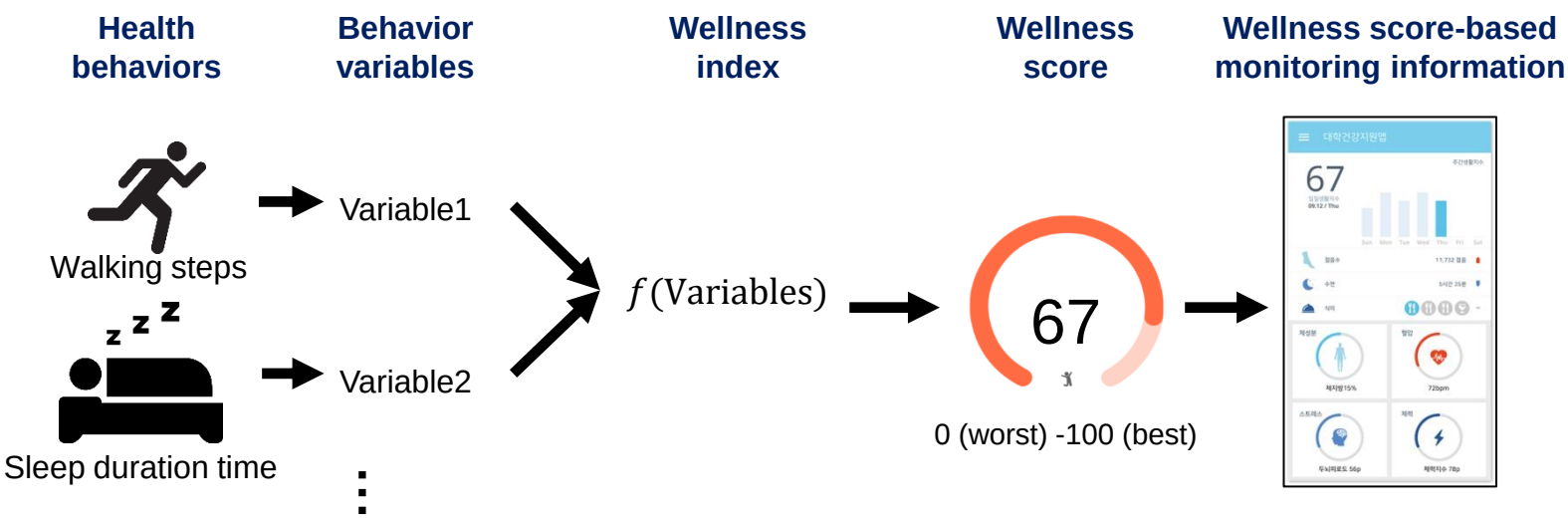


Source: Kim, K., Kim, K., Lim, C., and Heo, J., "Development of a Lifelogs-based Daily Wellness Score to Advance a Smart Wellness Service," *Service Science*, Vol. 10, No. 4, 408–422, 2018.

Onecare Service Development: Overview

- Necessity of wellness management support for college students
  - Wellness means lifestyle to maintain good mental and physical health (Myers et al. 2000)
  - Many students have unhealthy activity, sleep, and diet behaviors (Small et al. 2012)
  - Students need overall support to manage various behaviors

- Concept of Onecare



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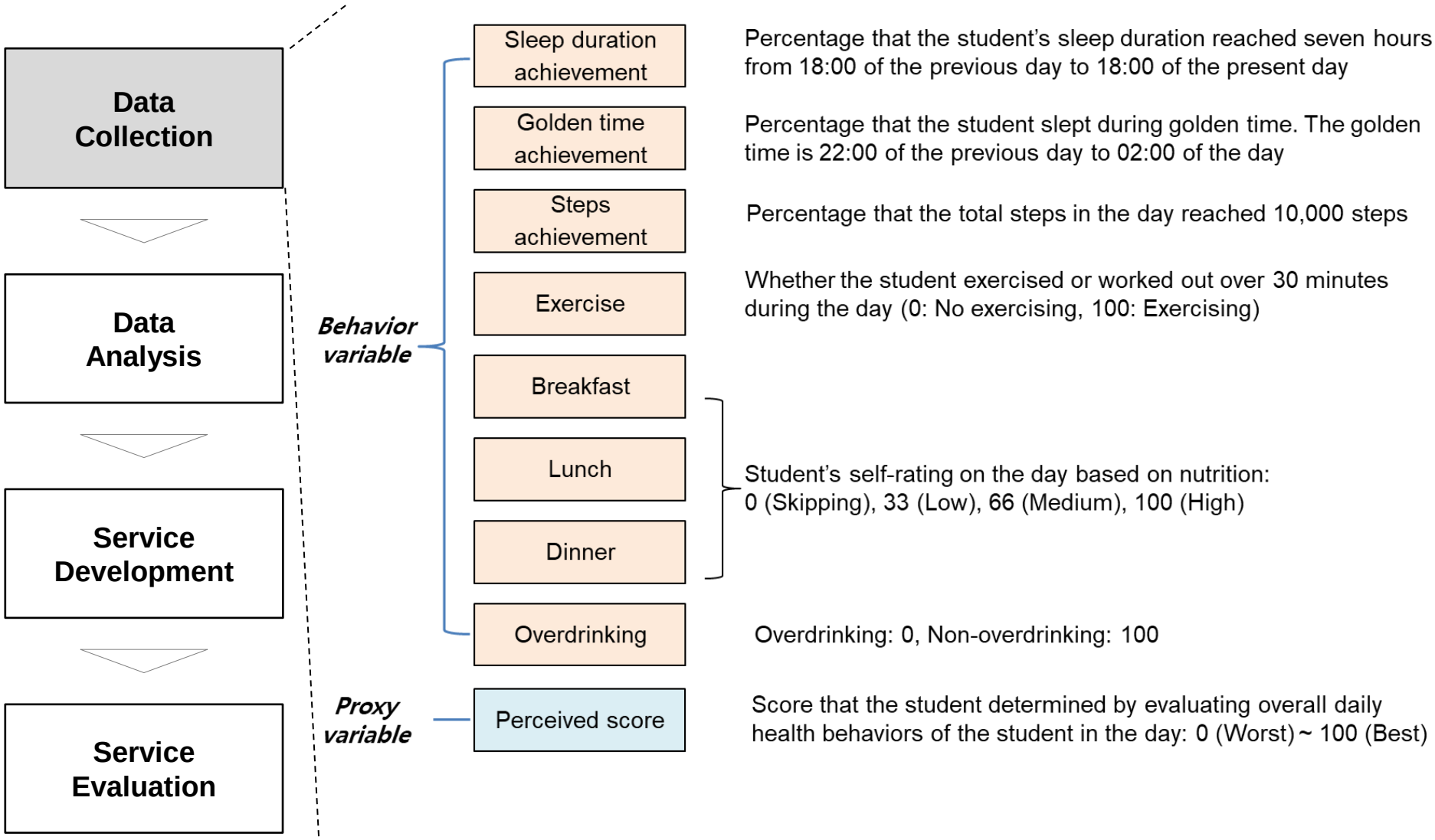
Onecare Service Development: Data Collection (1/2)



Onecare Service Development: Data Collection (2/2)

Data Collection

Data Analysis

Service Development

Service Evaluation

Behavior variable

- Sleep duration achievement
- Golden time achievement
- Steps achievement
- Exercise
- Breakfast
- Lunch
- Dinner
- Overdrinking

Proxy variable

- Perceived score

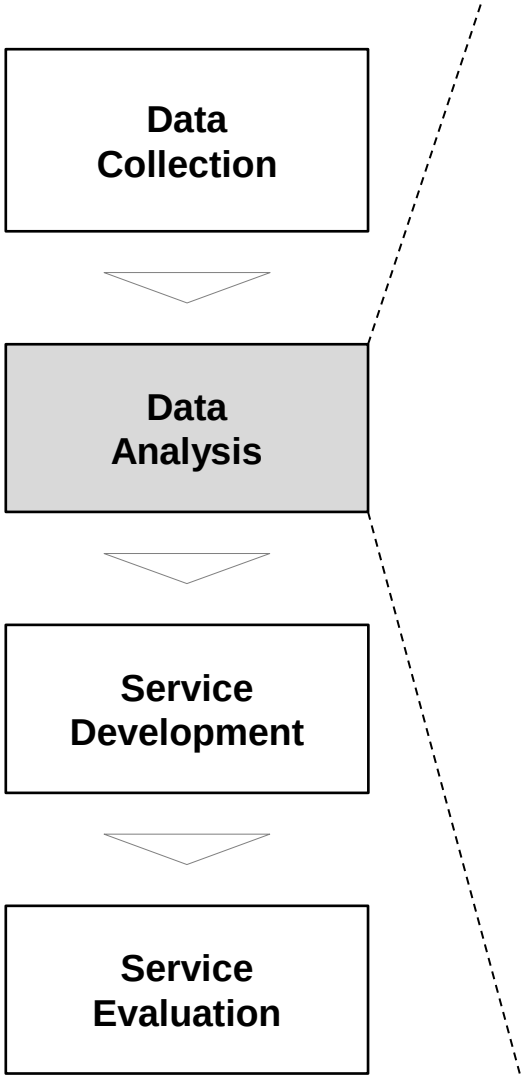
Automatic collection

Data entry of participants

4-week data set of 41 students

Person	Date	Breakfast	…
1	11/3	100	…
…	…	…	…
41	11/31	0	…

Onecare Service Development: Data Analysis (1/2)



Regression of Perceived Score on Behavior Variables

$$y_{it} = \beta_0 + \sum_{k=1}^{8} \beta_k x_{k,it} + \mu_i + u_{it}$$

Perceived score

Behavior variables

Wellness Index

0.219*Sleep duration achievement + 0.102*Golden time achievement + 0.095*Steps achievement + 0.135*Exercise + 0.151*Breakfast + 0.163*Lunch + 0.135*Dinner

(Range : 0~100)

Onecare Service Development: Data Analysis (2/2)

"Model building" "Search optimal setting for **x**"

$$y = f(\mathbf{x}, \boldsymbol{\theta}) + \varepsilon \quad \rightarrow \quad \hat{y}(\mathbf{x}) \quad \rightarrow \quad \underset{\mathbf{x} \in \Omega}{\text{optimize}} \ \hat{y}(\mathbf{x})$$

Regression of Perceived Score on Behavior Variables

$$y_{it} = \beta_0 + \sum_{k=1}^{8} \beta_k x_{k,it} + \mu_i + u_{it}$$

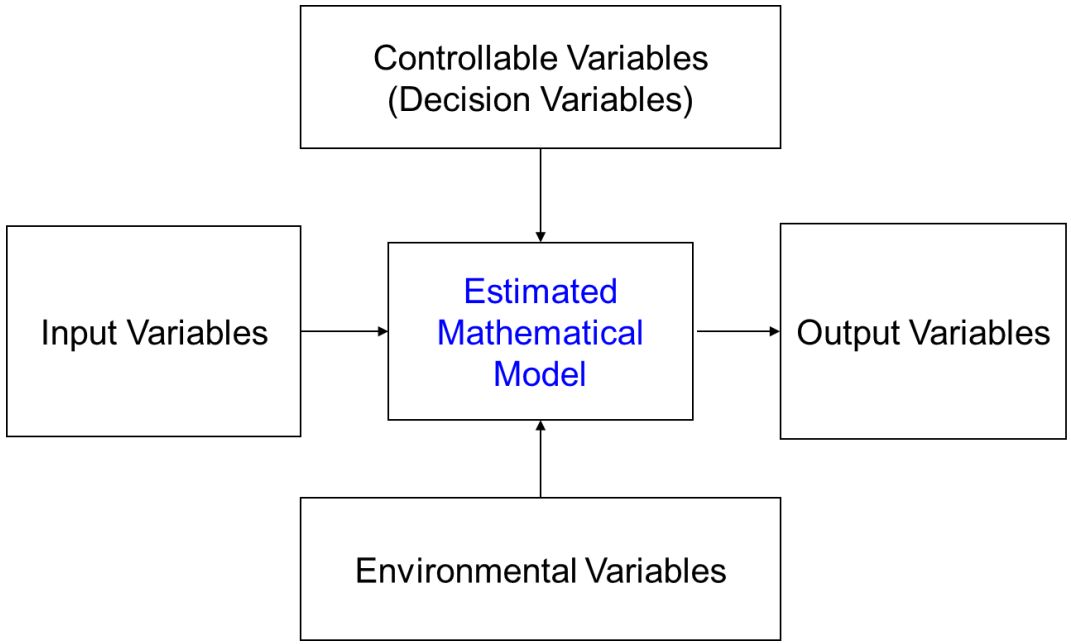
Perceived score

Behavior variables

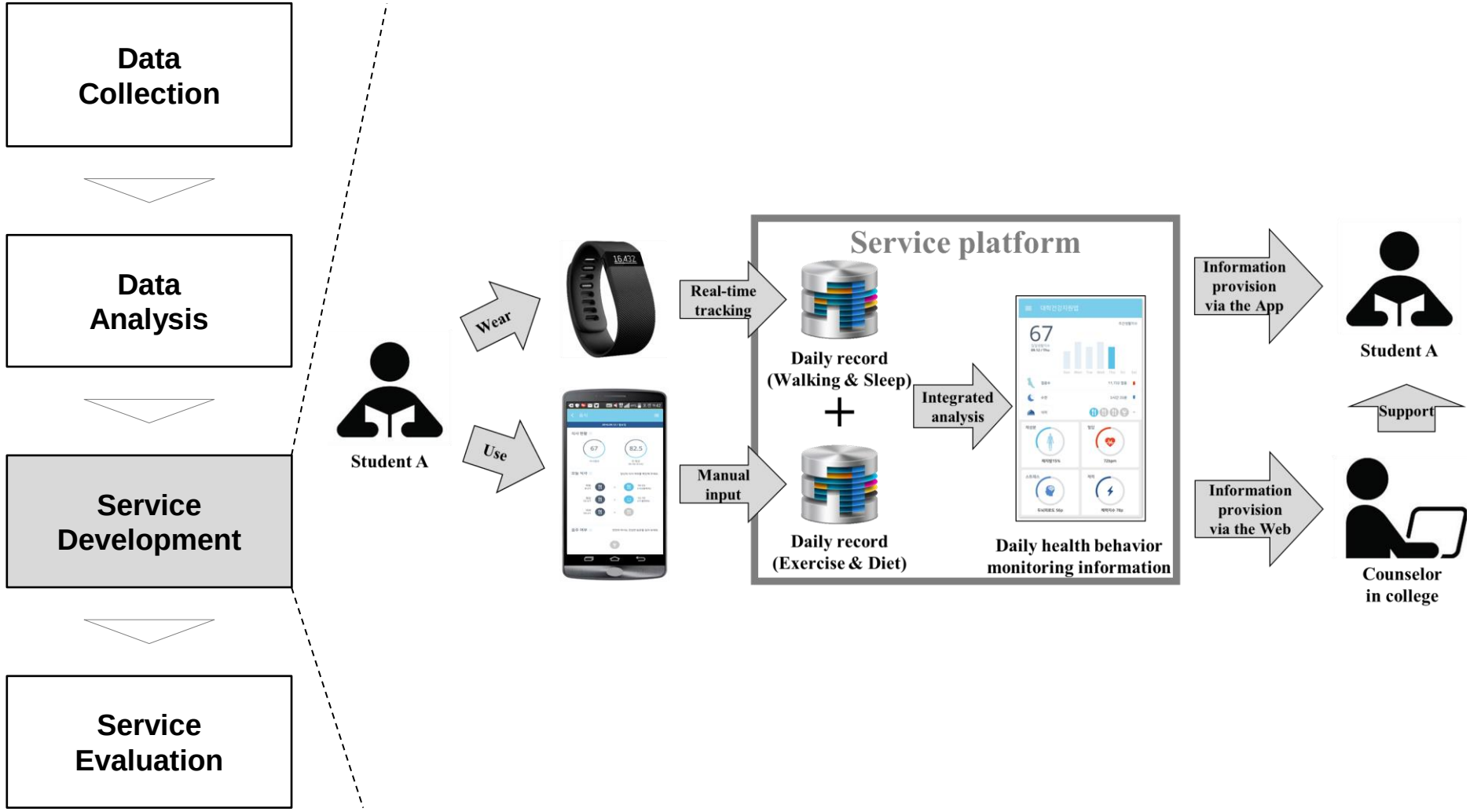
Wellness Index

0.219*Sleep duration achievement + 0.102*Golden time achievement + 0.095*Steps achievement + 0.135*Exercise + 0.151*Breakfast + 0.163*Lunch + 0.135*Dinner

(Range : 0~100)



Onecare Service Development: Service Development (1/3)

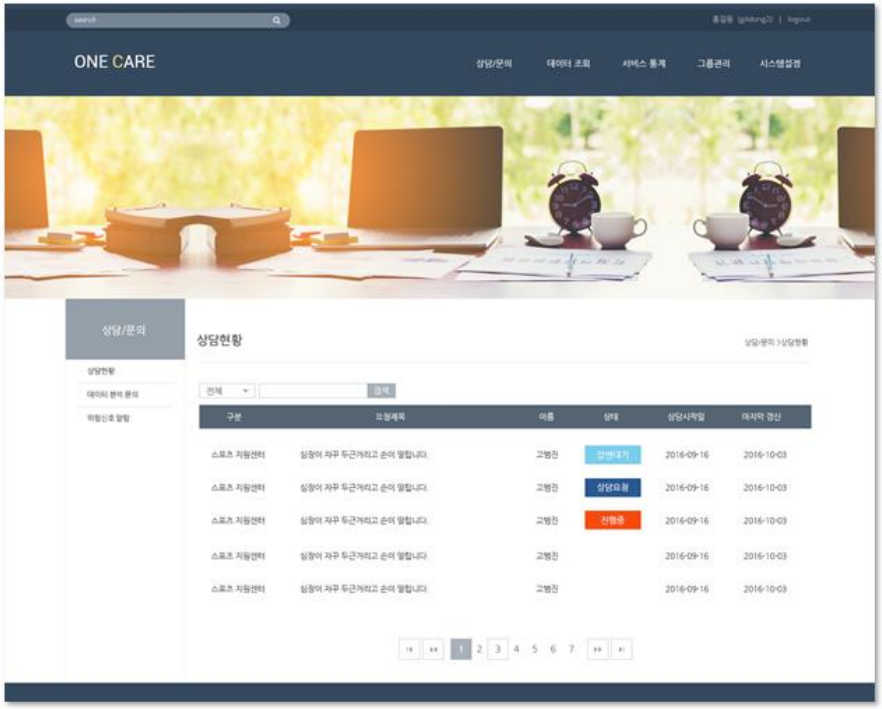


Onecare Service Development: Service Development (2/3)

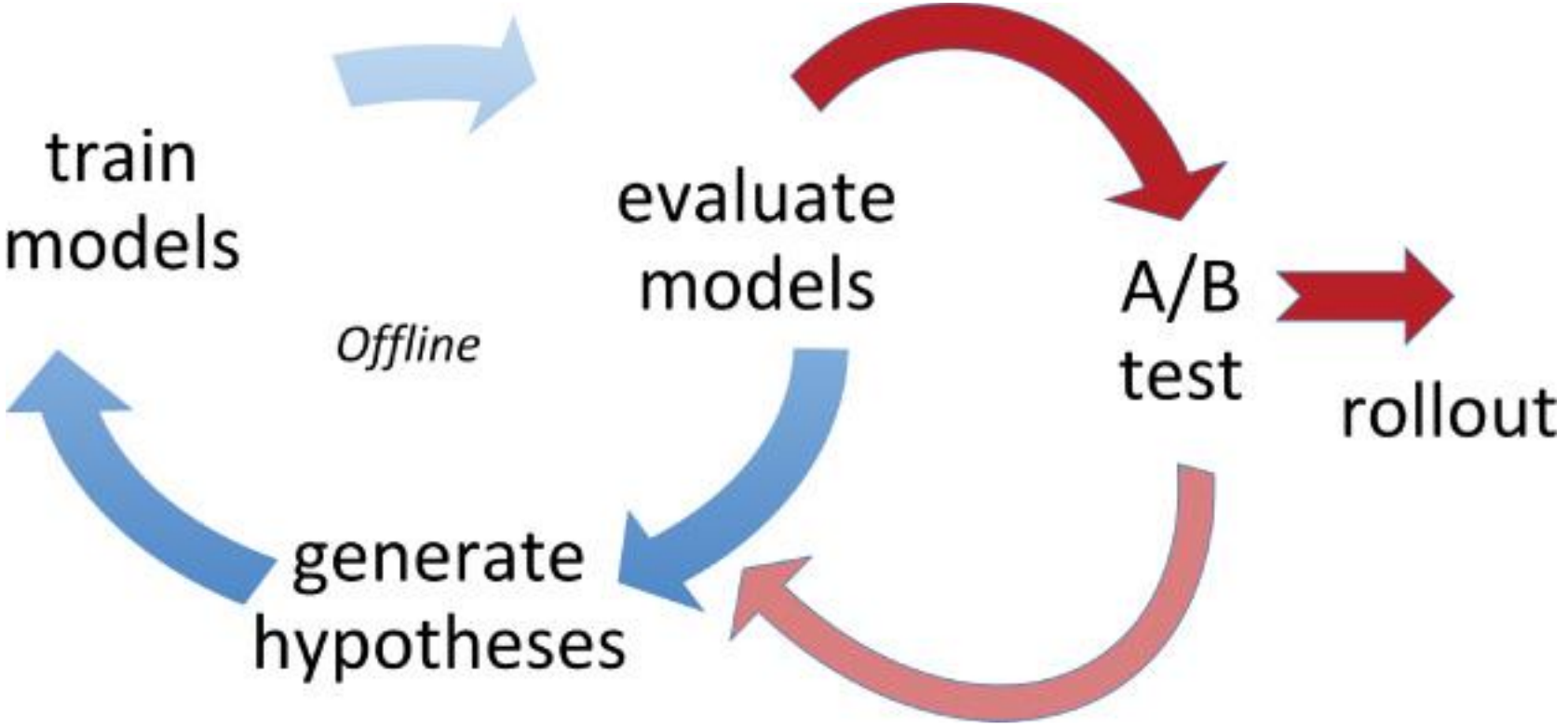
Onecare App for College Students

Onecare Service Development: Service Development (3/3)

Onecare Website for College Counselors

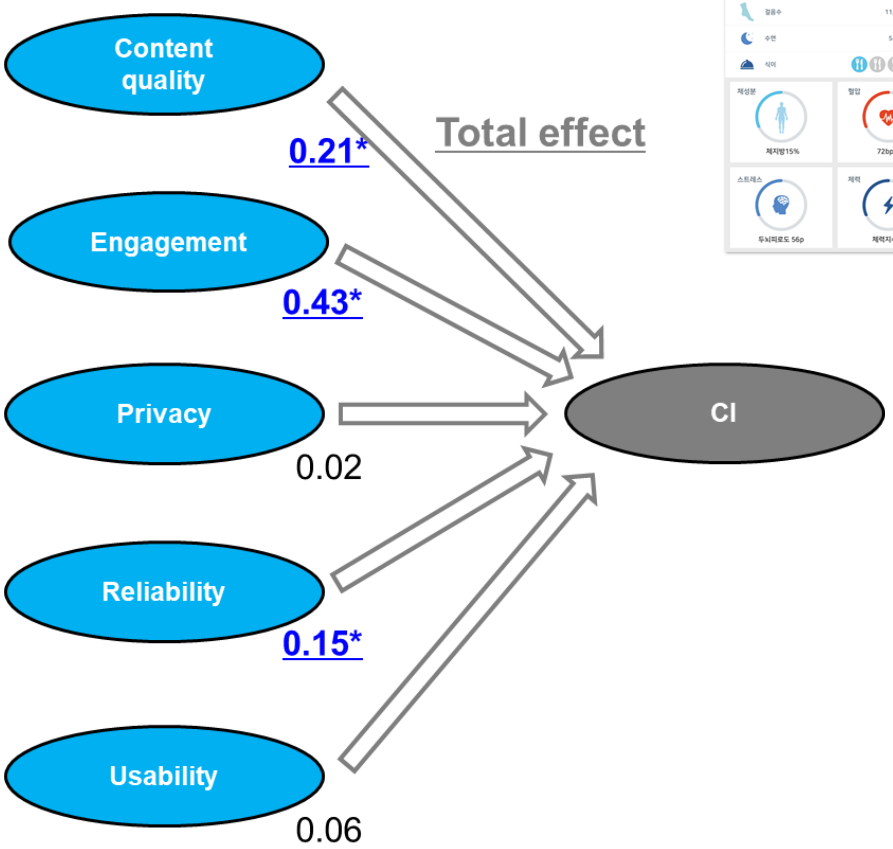


Verification, Validation, and Further Validation



Onecare Service Development: Service Evaluation (1/2)

191 survey responses



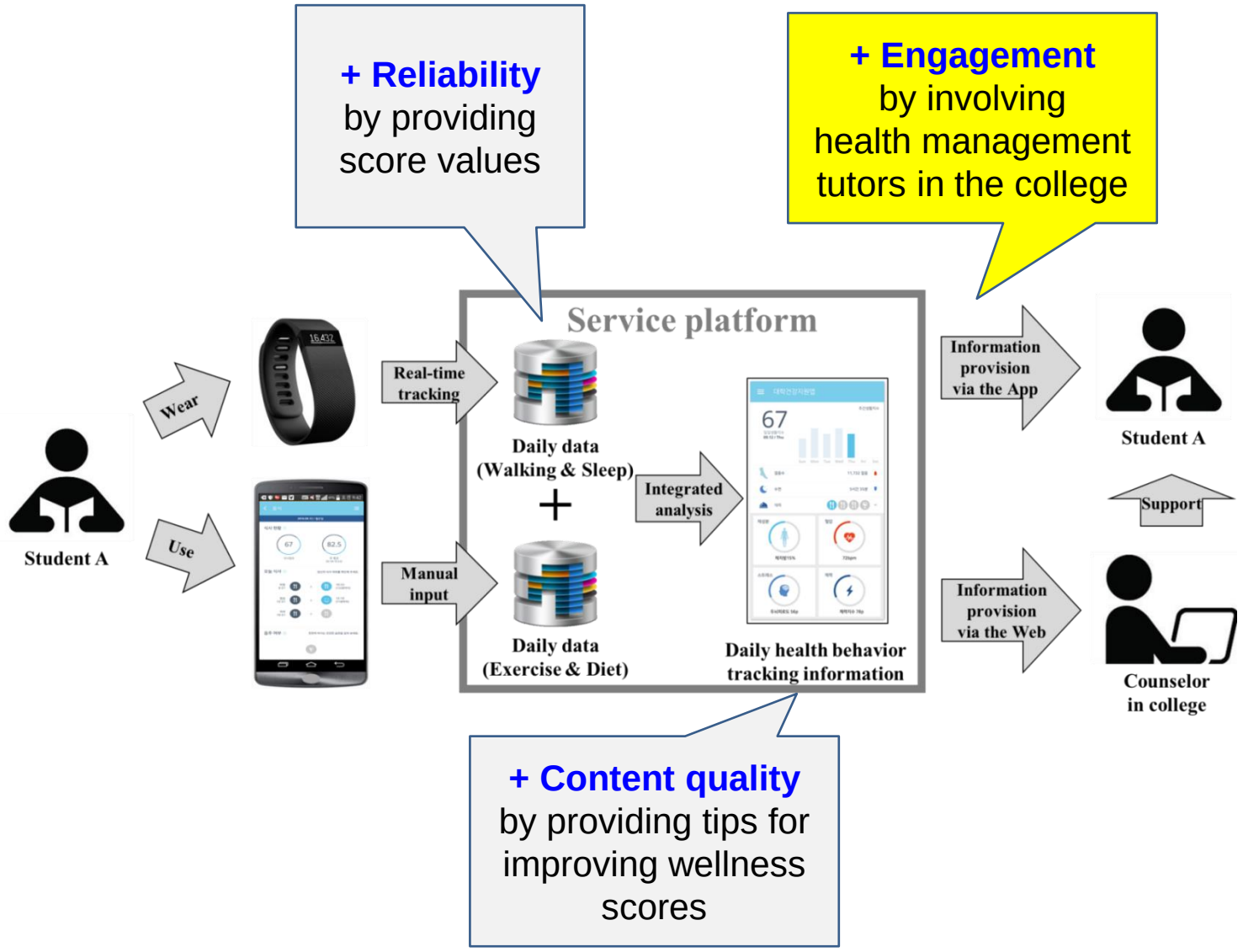
Finding

Engagement, Content quality, and Reliability are critical for CI

* p-value <0.05

Source: Kim, K., Kim, K., Lee, D., and Kim, M., "Identification of Critical Quality Dimensions for mHealth Services: A Case Study of Onecare Service," International Journal of Information Management, Vol. 46, 187–197, 2019.

Onecare Service Development: Service Evaluation (2/2)



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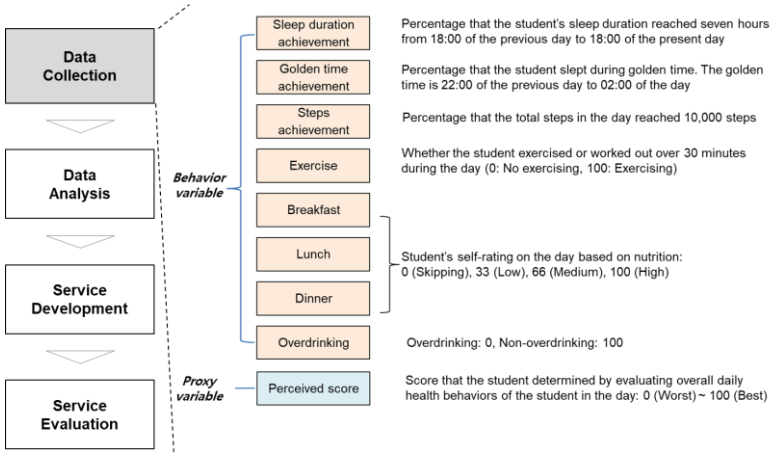
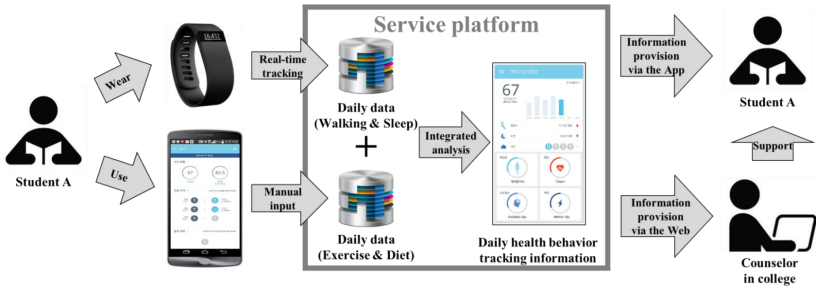
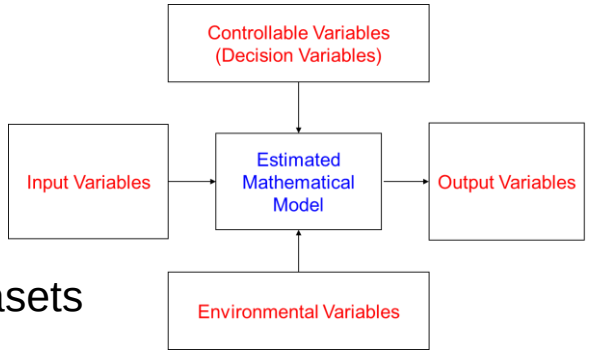
Discussion

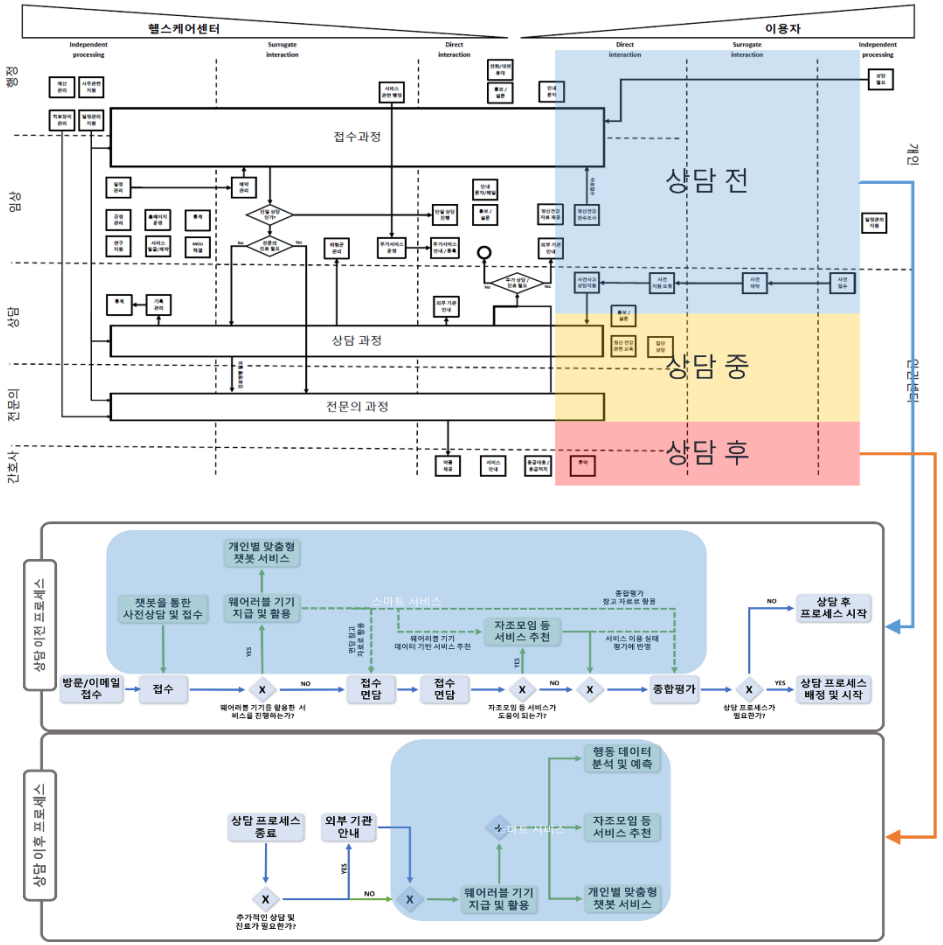






- Health behavioral data for healthcare services
- Matching the heterogeneous yet related health-related datasets
- Difference between the individual processes
- Method to learn the commonalities and difference between the individual processes
- Use of reliable measures to be matched with behavioral data
- Use of mentality measures with behavioral data for mental healthcare
- Mediating the different stakes of data-related stakeholders for service

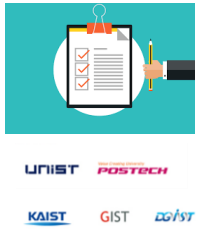
Attempt in UNIST: Students Clustering for Counseling/Advising



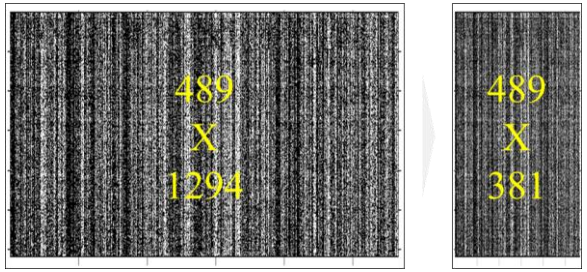
Attempt in UNIST: Students Clustering for Counseling/Advising

1. Collection of text data on the topic in question
2. Semi-automatic semantic identification of significant word-features
3. Unsupervised learning of the data with selected word-features
4. Interpretation

1



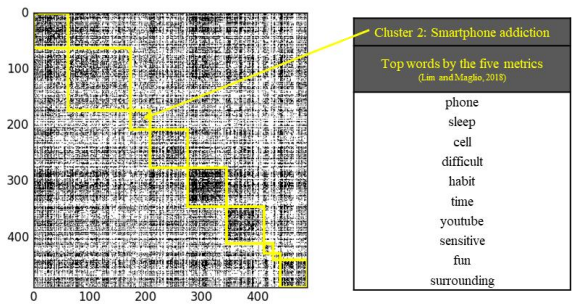
2



4

- 스트레스 (Stress)
- 완벽주의 (Perfectionism)
- 스마트폰 (Smartphone)
- 너무피곤 (Tiredness)
- 인간관계 (Relationship)
- 놀고싶어 (WantPlay)
- 귀차니즘 (Laziness)
- 자기안심 (Self-justification)
- 일이많음 (TooManyWorks)

3



Attempt in UNIST: Students Clustering for Counseling/Advising

Cluster 0. 스트레스 (Stress)

Cluster 1. 완벽주의 (Perfectionism)

Cluster 2. 스마트폰 (Smartphone)

Cluster 3. 너무피곤 (Tiredness)

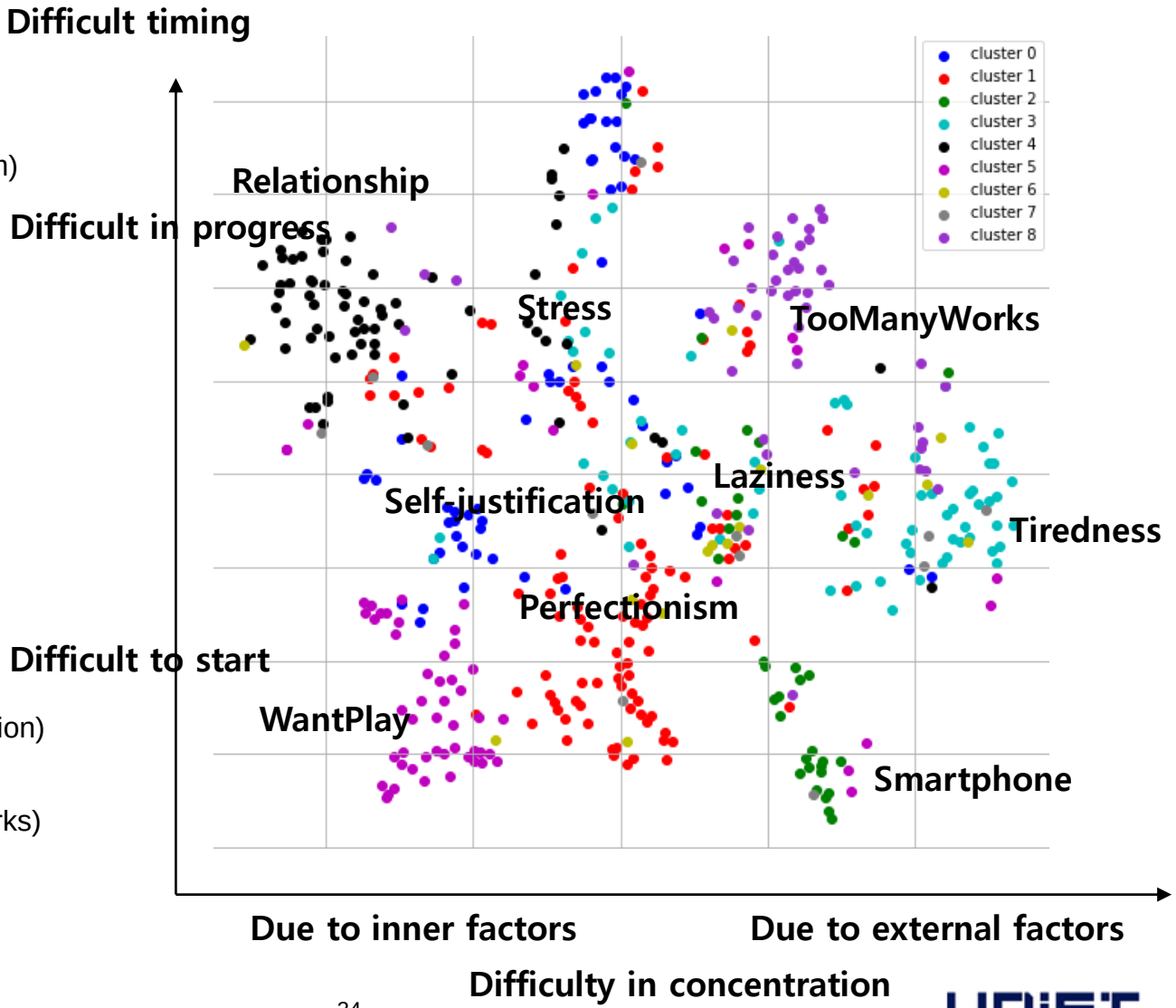
Cluster 4. 인간관계 (Relationship)

Cluster 5. 놀고싶어 (WantPlay)

Cluster 6. 귀차니즘 (Laziness)

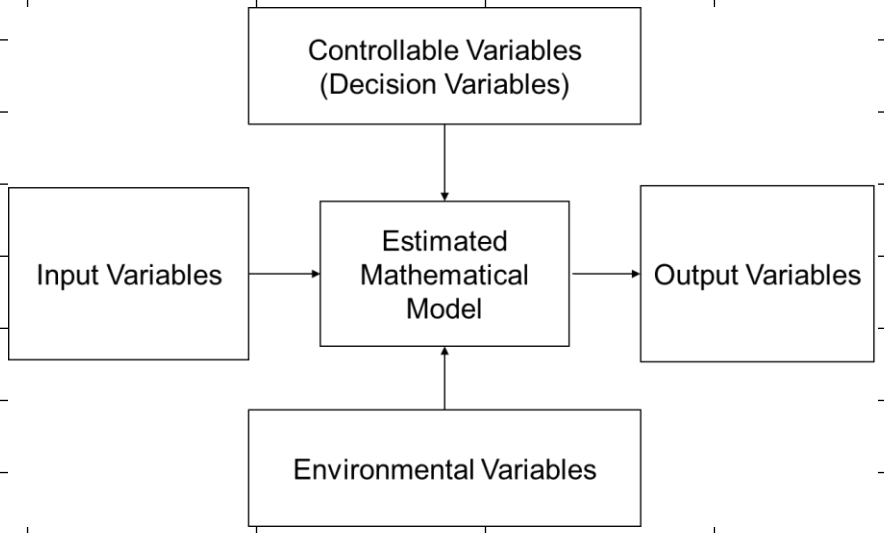
Cluster 7. 자기안심 (Self-justification)

Cluster 8. 일이많음 (TooManyWorks)



Behavioral Data for Personal Process Management

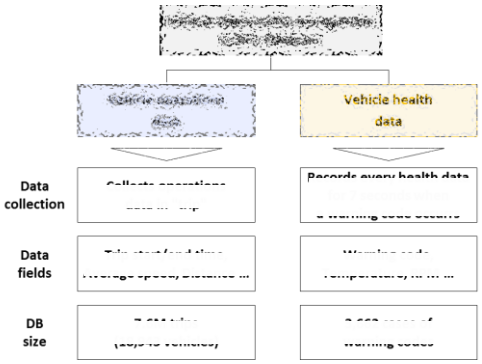
	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2	…					…
Customer 3	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…	…	…	…	…	…
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…



Personal Process Management:

in the Context of Driving Task Support

Personal Process Management in the Context of Driving Support



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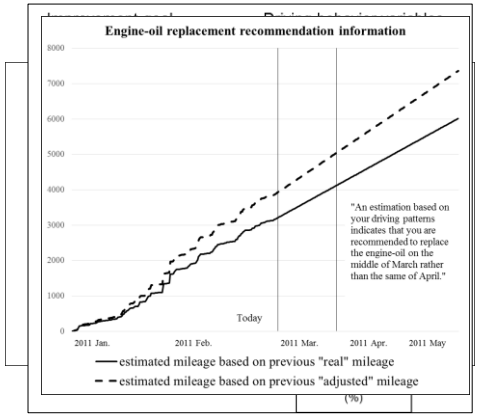
Average mileage per trip (km)	7.62	5.96	...	10.02
Ratio of short trip (< 18km)	91.08	97.64	...	87.36
Average of low speed (< 29 km/h) ratio per trip	73.18	72.87	...	68.15
Engine oil deterioration indicator 1	284	159	...	34
Engine oil deterioration indicator 2	32.49	41.62	...	39.08
Tire wear indicator 1	0.018	0.018	...	0.019
...	...	...	...	...

Driving process characteristics

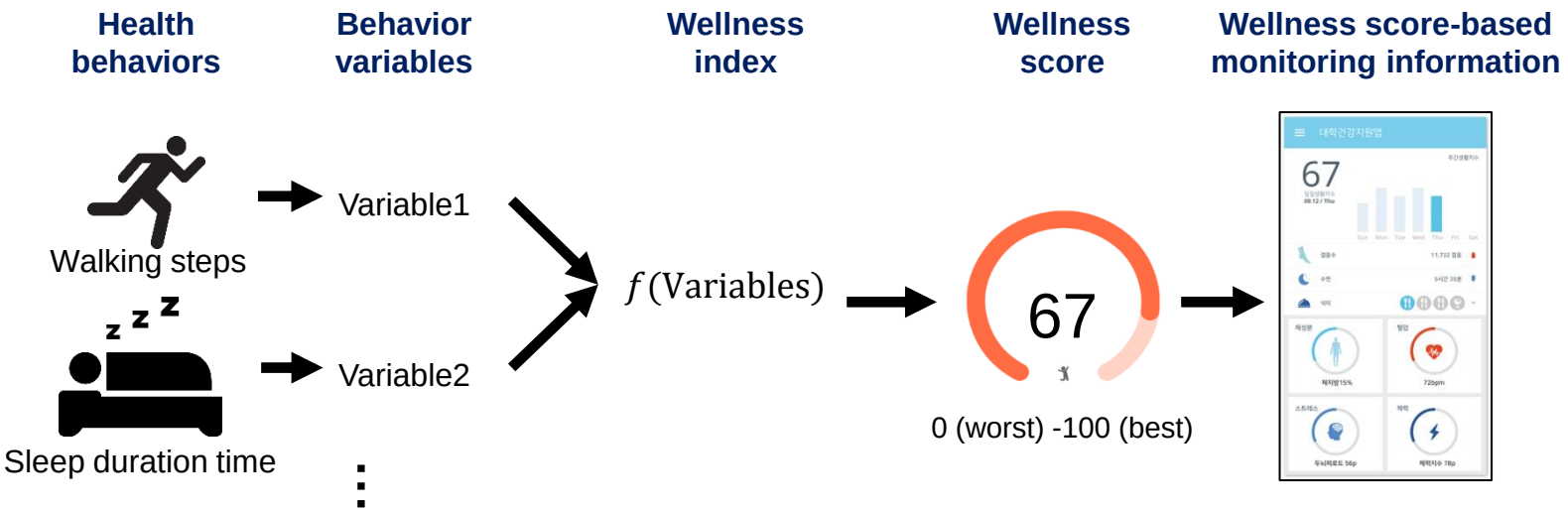
Driving process analysis

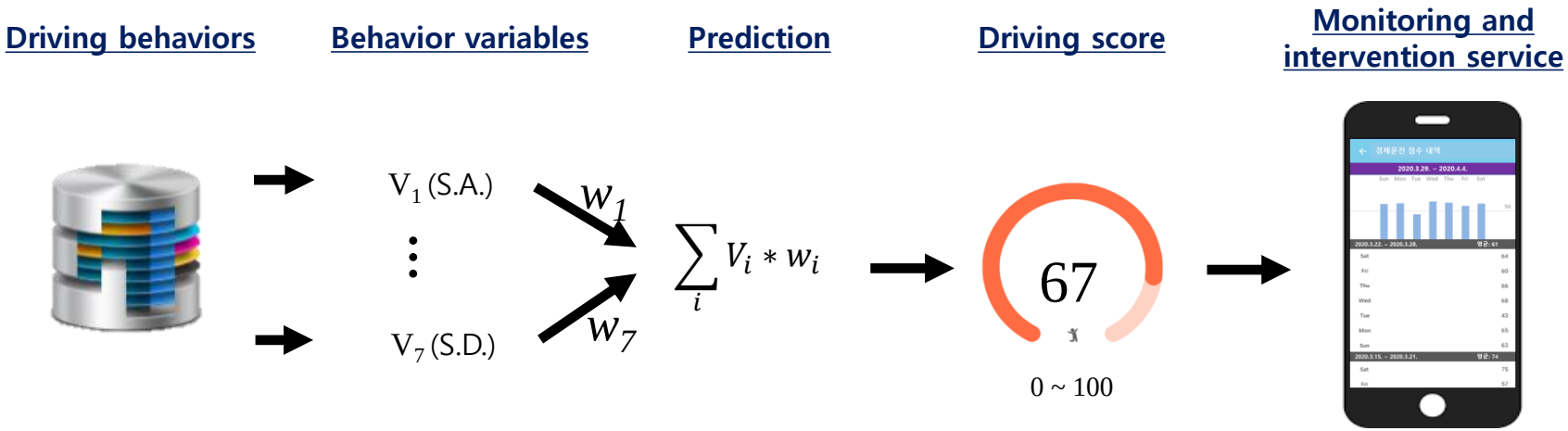


Information for process improvement

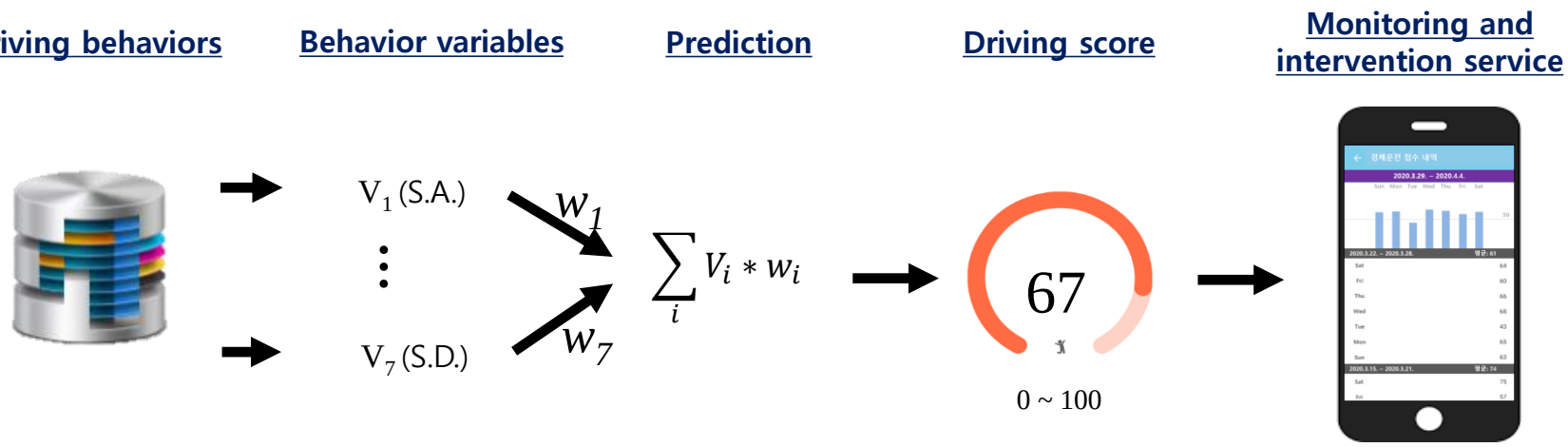
Reference: “Customer Process Management” (Lim et al., 2019; *JoSM*)

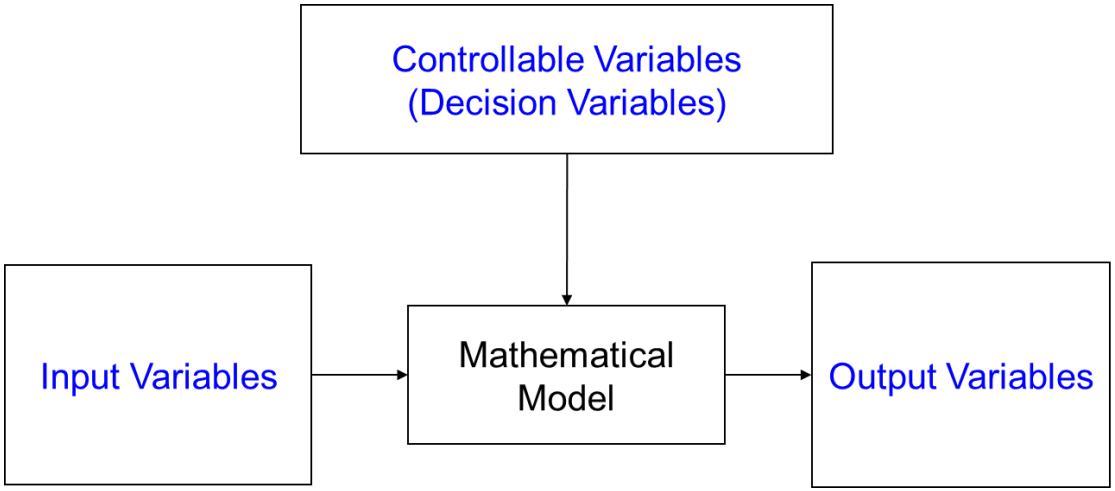
Driving Process Management: Eco Driving Context



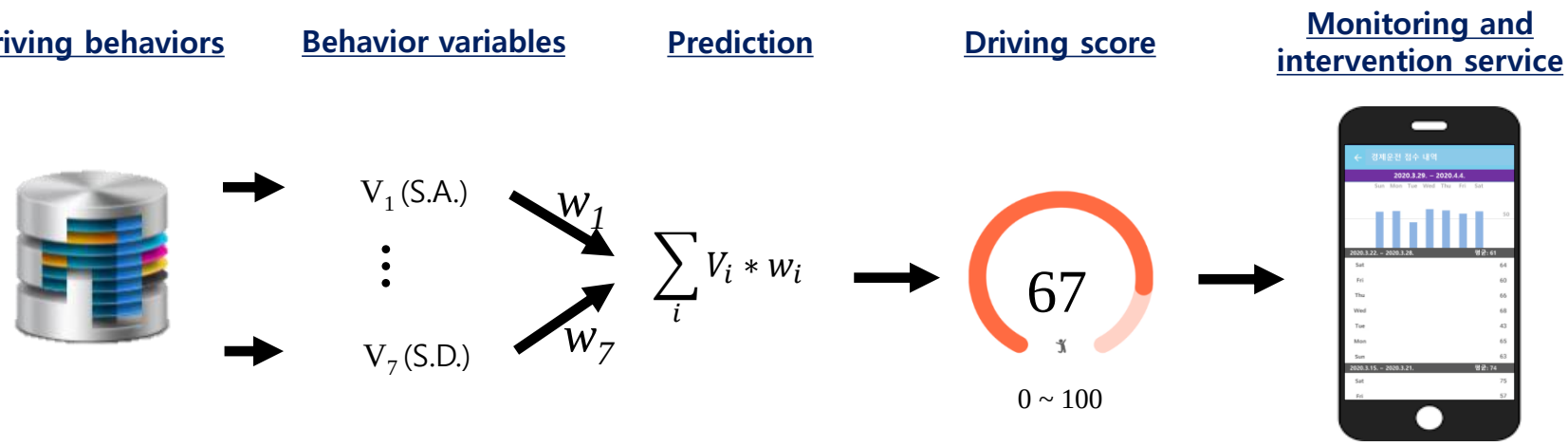


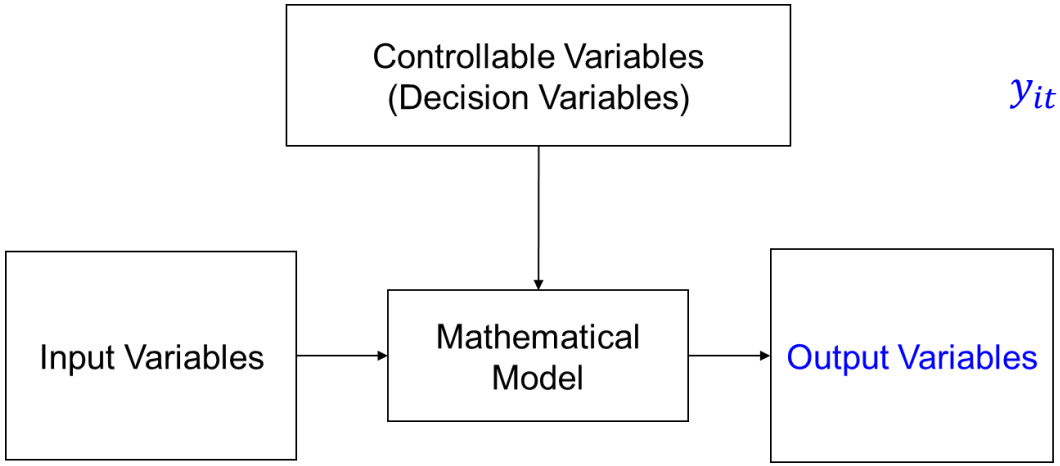
Driving Process Management: Eco Driving Context





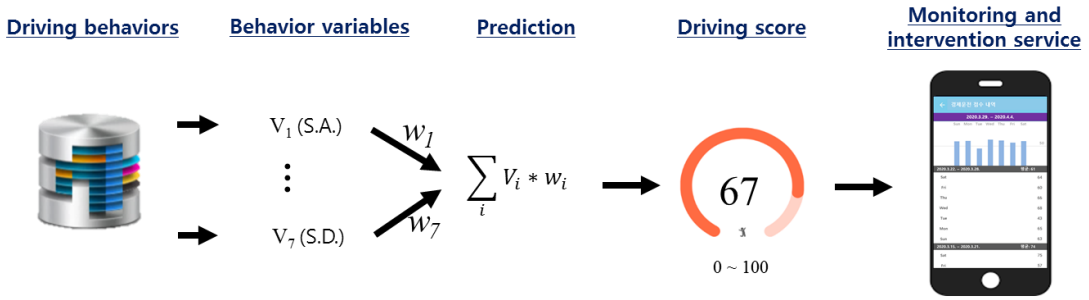
Driving Process Management: Eco Driving Context

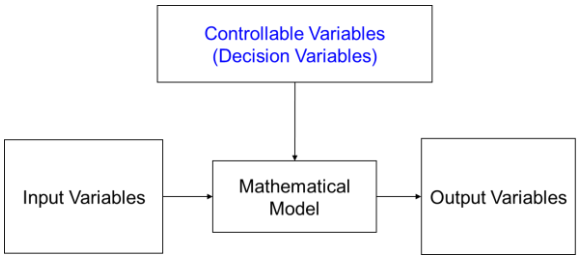




$$y_{it} = standardize(-FPK_{it}) = \left[\frac{\{-FPK_{it} - mean(-FPK_{i*})\}}{sd(-FPK_{i*})}\right]$$

Driving Process Management: Eco Driving Context





Behavior	Description
Frequent Stops and Goes (FSG)	Within 3 seconds, acceleration starts from 0km/h and then the speed becomes 0km/h again.
High-speed Cruising (HC)	The following conditions are satisfied for at least five seconds: (1) the average speed is no less than 100 km/h; (2) the standard deviation of speed is no more than 1.5km/h; (3) the maximum of the instantaneous acceleration is no more than 1 km/h/s; and (4) the average acceleration ranges from -0.25km/h/s to 0.25km/h/s
Low-speed Running (LR)	The average speed is at most 23km/h for no less than 60 seconds
Prolonged Acceleration (PA)	The acceleration continues for at least 5 seconds
Prolonged Idling (PI)	The idling continues for at least 60 seconds
Sharp Acceleration (SA)	The instantaneous acceleration is no less than 4km/h/s for at least 1 second
Sharp Deceleration (SD)	The instantaneous acceleration is no more than -5km/h/s for at least 1 second

$$x_{k,it} = \frac{behavior\_occurrence_{k,it}}{distance_{it}}$$

Reference: Chen, C., Zhao, X., Yao, Y., Zhang, Y., Rong, J., & Liu, X. (2018). Driver's Eco-Driving Behavior Evaluation Modeling Based on Driving Events. *Journal of Advanced Transportation*, 2018.

Driving Process Management: Eco Driving Context

- A case study using the data of buses in South Korea

2,629 Trip Observations from 10 Buses

Driving and fuel consumption data

Bus	Trip	X			y ST(-FPK)
		SA	...	SD	
1	1	0.281	...	0.018	0.114
	...	...	...	...	...
	323	1.424	...	0.005	-0.145
...	...	...	...	...	...
10	1	0.332	...	0.012	-0.132
	...	...	...	...	...
	491	0.769	...	0.347	1.025

Split

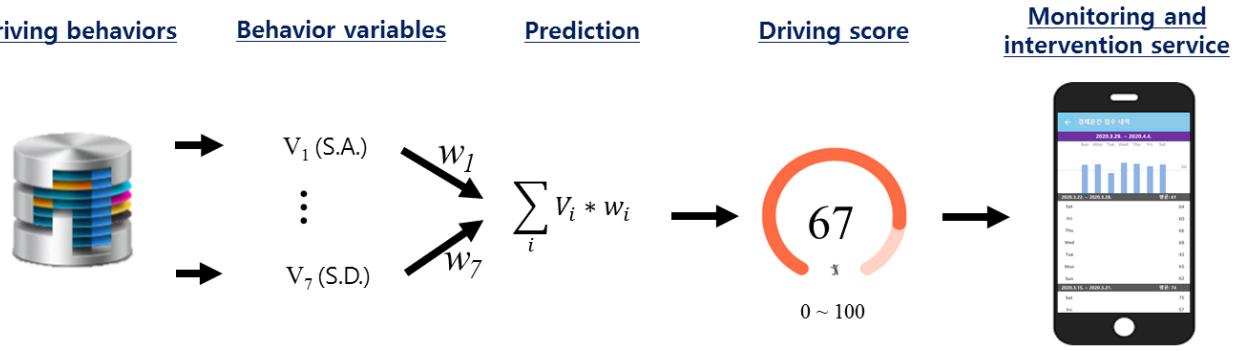
Training

80% (2,100)

Test

20% (529)

Driving Process Management: Eco Driving Context



Weight estimation of the Bus 1

Variable	Descriptive statistics				Estimation results	
	Mean	Standard deviation	Min	Max	Estimate	Standard error
Standardize(-FPK)	0.000	1.000	-7.011	1.996	-	-
SA	0.704	2.428	0.000	21.231	~~0.323~~	0.171
SD	0.620	2.101	0.000	19.385	-0.573*	0.190
PA	0.526	0.318	0.000	1.667	-0.440*	0.197
PI	0.022	0.040	0.000	0.375	~~-1.540~~	1.335
LR	0.067	0.050	0.000	0.357	-8.895*	1.220
HC	0.174	0.117	0.000	0.556	-0.910*	0.462
FSG	0.011	0.071	0.000	1.077	-3.297*	0.695
(intercept)	-	-	-	-	1.184	0.170

* The estimate had p-value of below 0.05

Average R^2 (STD): 0.66 (0.11)

Scaling

$1.18 - 0.57*DS - 0.44*LA - 8.90*LS - 0.91*HS - 3.30*SS$

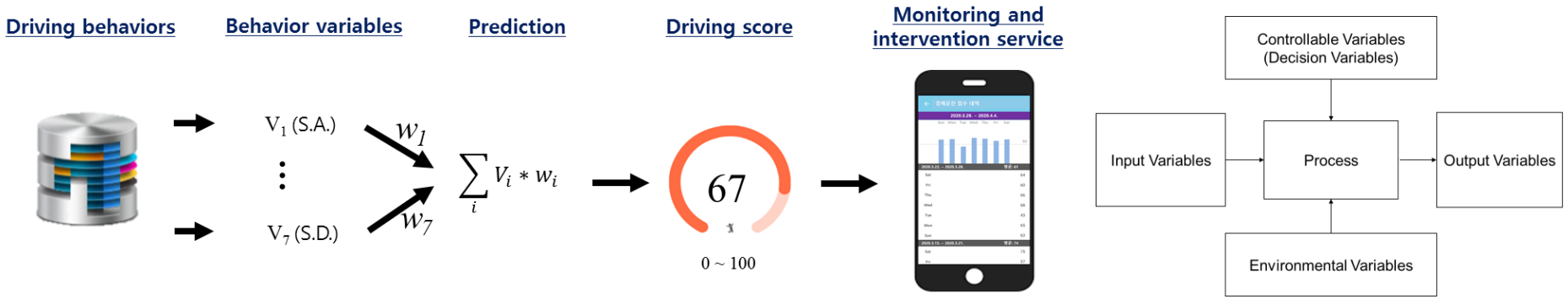
-10.93 ~ 1.28

Min-Max normalization

$100 - 1.79*DS - 4.98*LA - 75.30*LS - 8.96*HS - 23.67*SS$

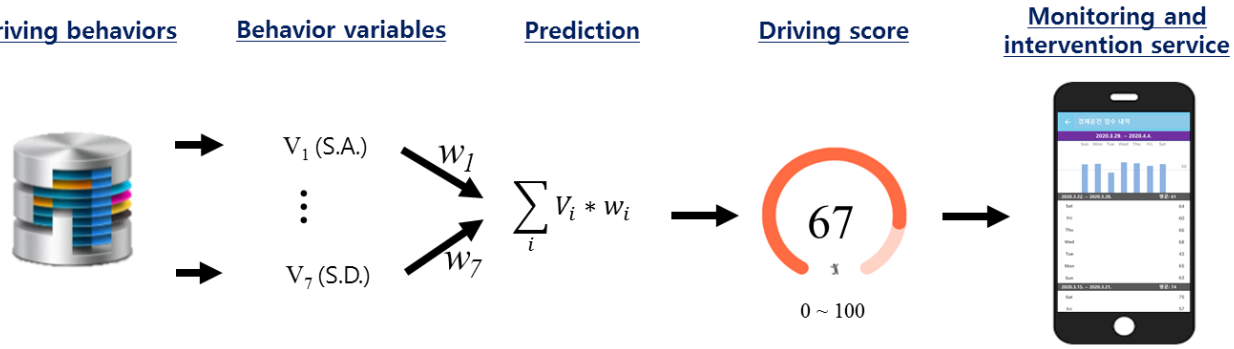
0 ~ 100

Driving Process Management: Eco Driving Context



Bus	Trip	Eco driving score	Fuel consumption Per Km	Driving behaviors (Weight)						
				SA (0.0)	SD (-1.79)	PA (-4.98)	PI (0.0)	LR (-75.30)	HC (-8.96)	FSG (-23.67)
1	Good	89	0.199	2.030	1.910	0.580	0.020	0.050	0.070	0.000
	Poor	32	0.394	17.313	15.688	0.125	0.375	0.313	0.000	0.25
Bus	**Trip**	**Eco driving score**	**Fuel consumption Per Km**	**SA (0.0)**	**SD (-38.97)**	**PA (-7.44)**	**PI (-32.43)**	**LR (0.0)**	**HC (-14.84)**	**FSG (0.0)**
2	Good	99	0.218	0.000	0.000	0.037	0.000	0.000	0.074	0.000
	Poor	51	0.331	0.524	0.62	1.857	0.143	0.286	0.429	0.048

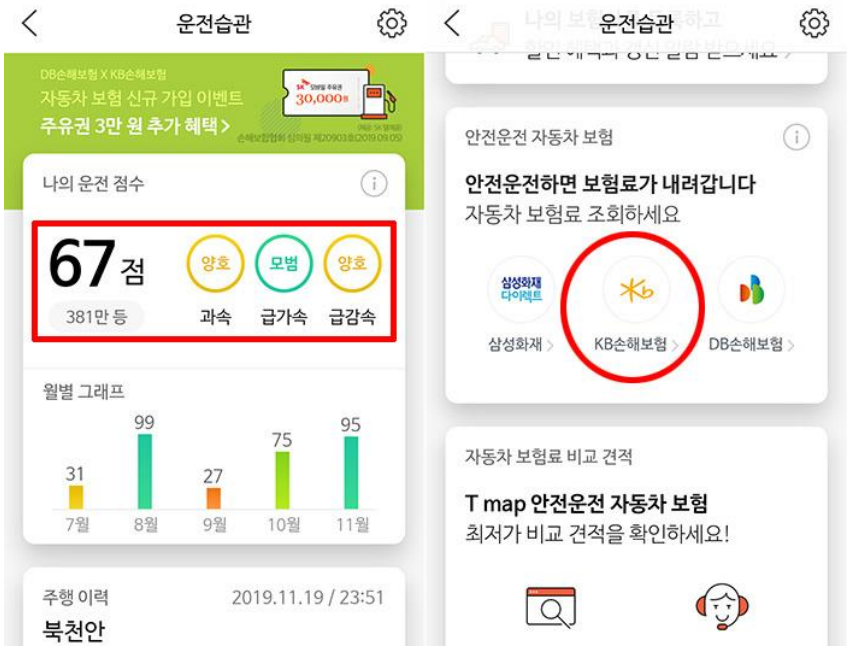
Driving Process Management: Eco Driving Context

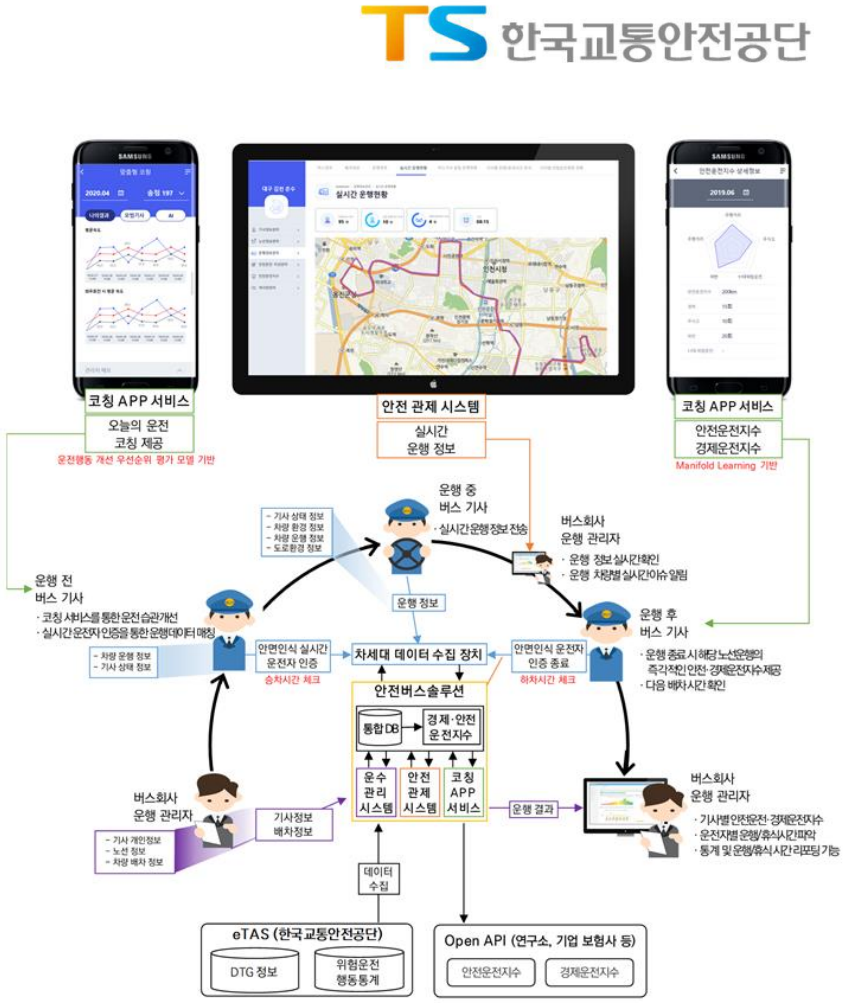


Bus	Trip	Eco driving score	Fuel consumption Per Km	Driving behaviors (Weight)						
				SA (0.0)	SD (-1.79)	PA (-4.98)	PI (0.0)	LR (-75.30)	HC (-8.96)	FSG (-23.67)
1	Good	89	0.199	2.030	1.910	0.580	0.020	0.050	0.070	0.000
	Poor	32	0.394	17.313	15.688	0.125	0.375	0.313	0.000	0.25

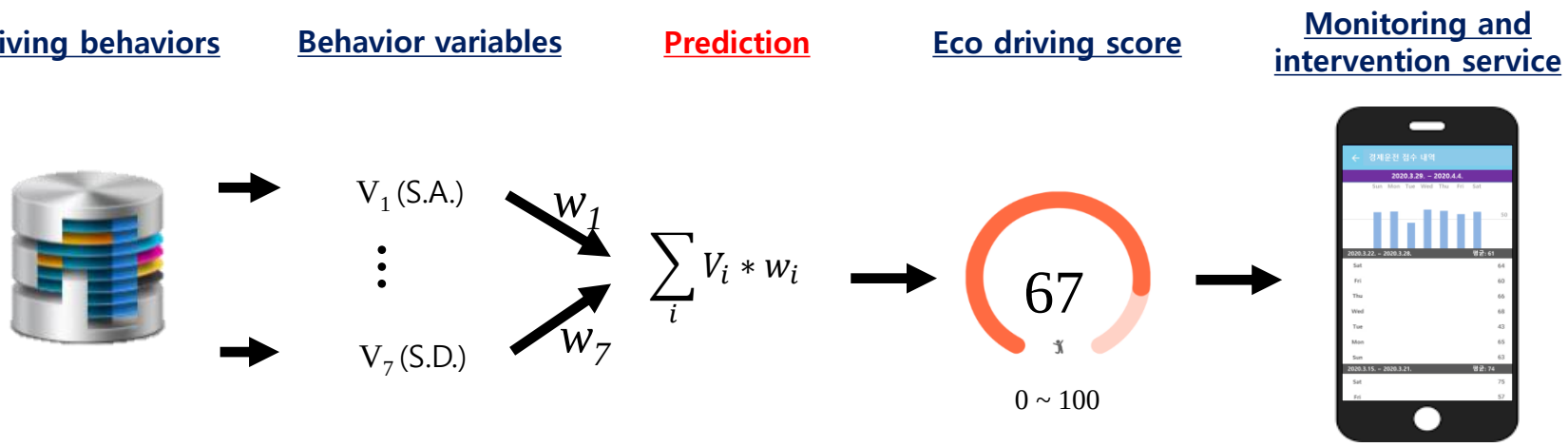
Bus	Trip	Variable effect and value	Driving behaviors						
			SA	SD	PA	PI	LR	HC	FSG
1	Poor	Absolute weight	0	1.79	4.98	0	75.30	8.96	23.67
		Variable value	17.313	15.688	0.125	0.375	0.313	0.000	0.25
		Impact	0	**28.082**	0.623	0.0	**23.569**	0.000	5.918

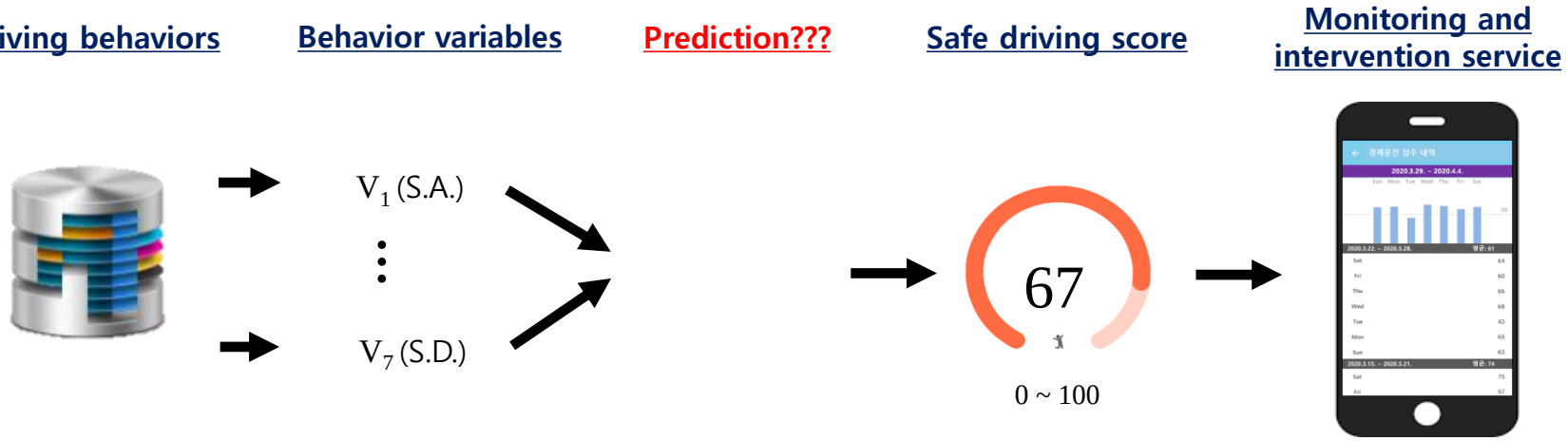
Driving Process Management: Safe Driving Context



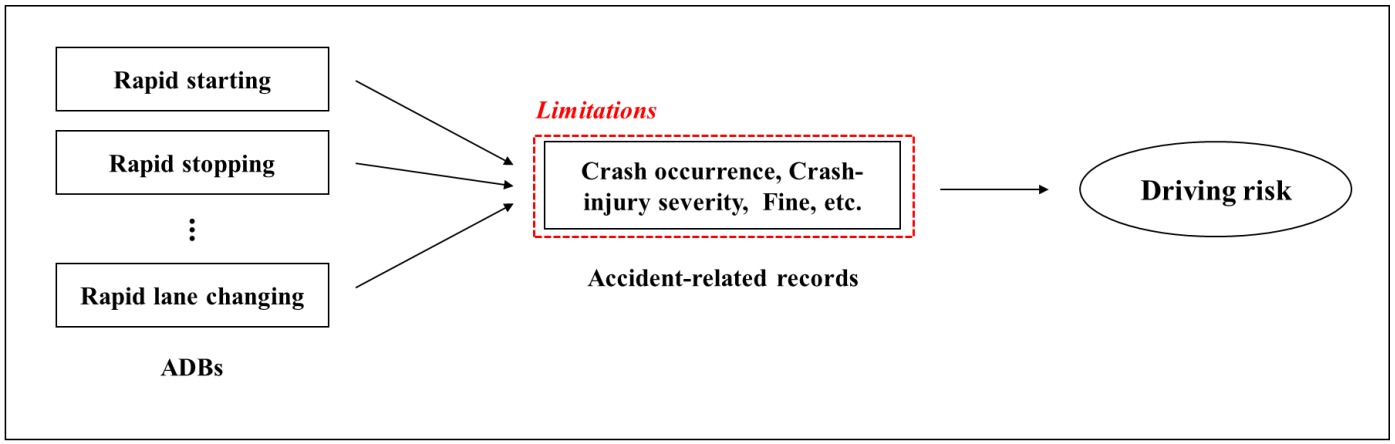


Existence vs. Nonexistence of the Labels

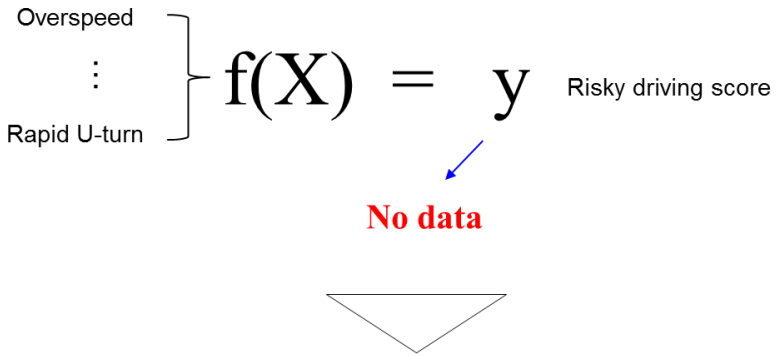




Driving Process Management: Safe Driving Context

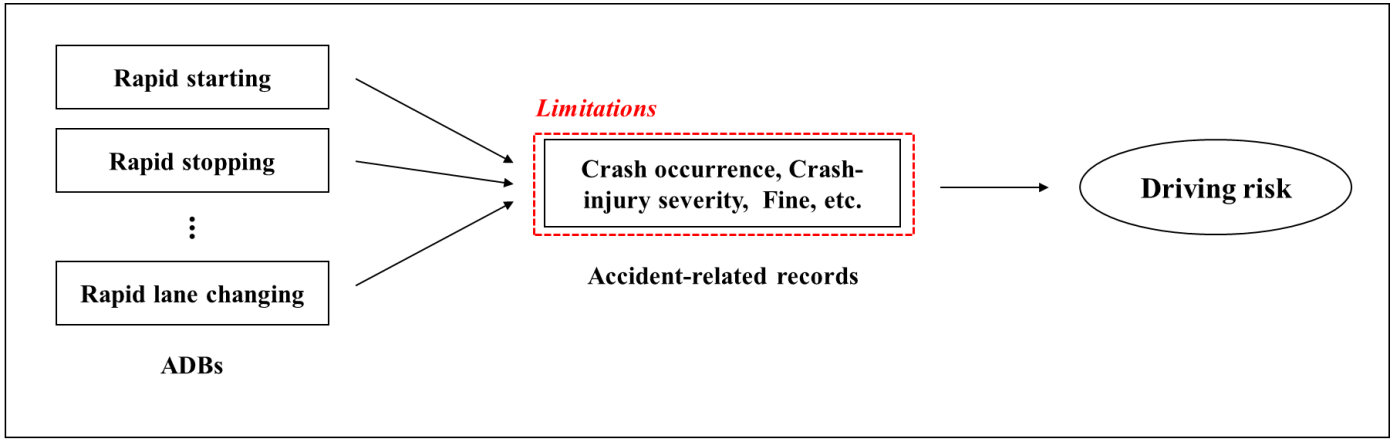


Limitation 1: Accident-related records are imperfect surrogate measures of driving risk
Limitation 2: Accident-related records are unreliable due to recording errors and reporting issues
Limitation 3: Accident-related records are difficult to acquire



Estimating "f(X) = y" is impossible

Driving Process Management: Safe Driving Context



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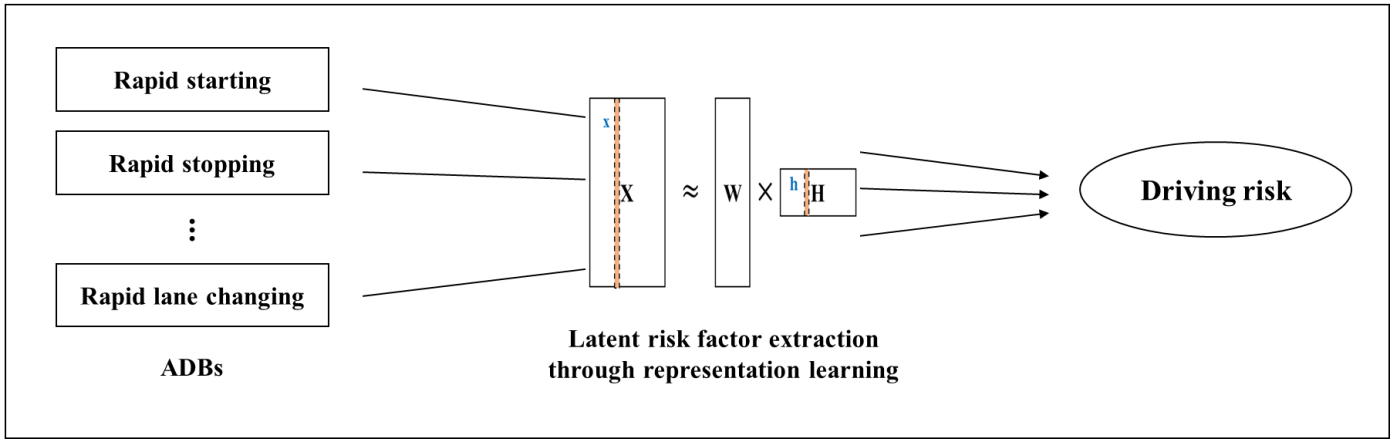
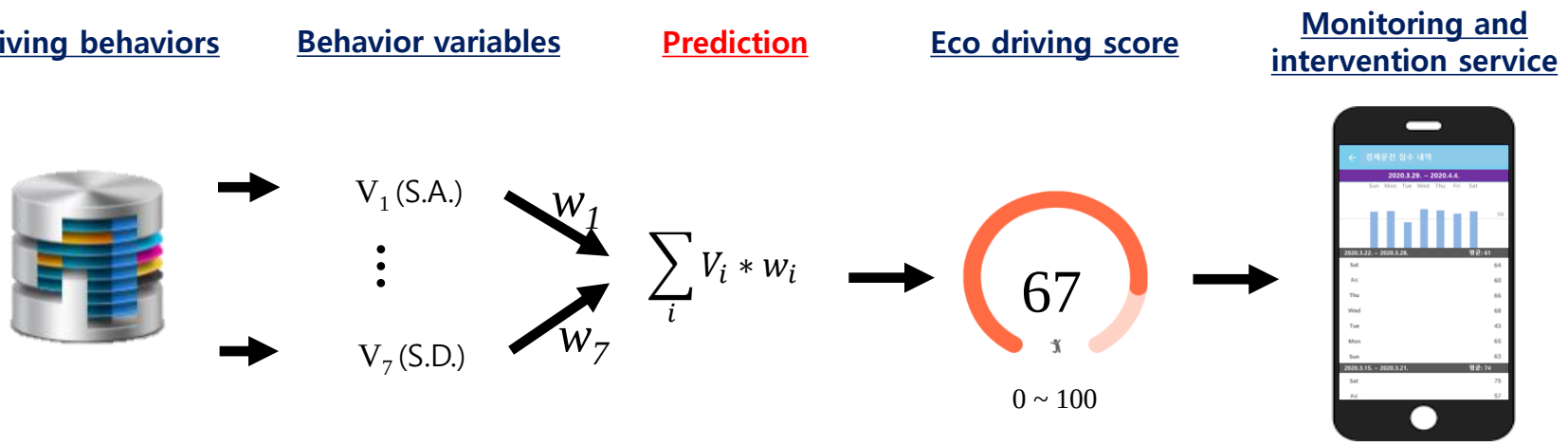
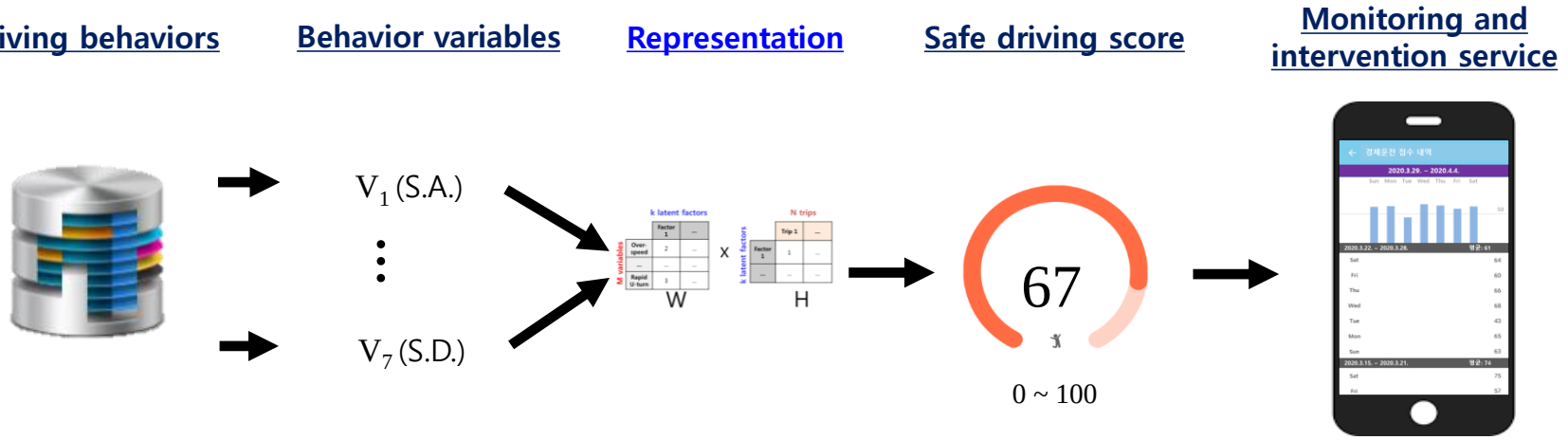


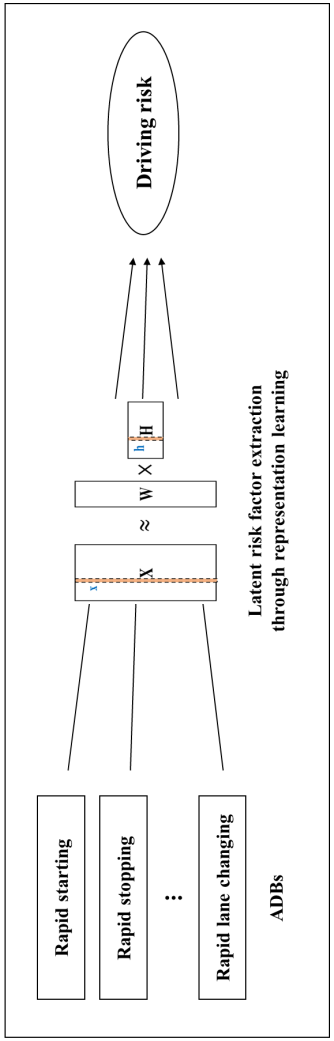
Reference: Seo, H., Shin, J., Kim, K., Lim, C. and Bae, J., "Driving Risk Assessment using Nonnegative Matrix Factorization with Driving Behavior Records," *IEEE Transactions on Intelligent Transportation Systems*, Accepted for Publication, 2022.

Existence vs. Nonexistence of the Labels



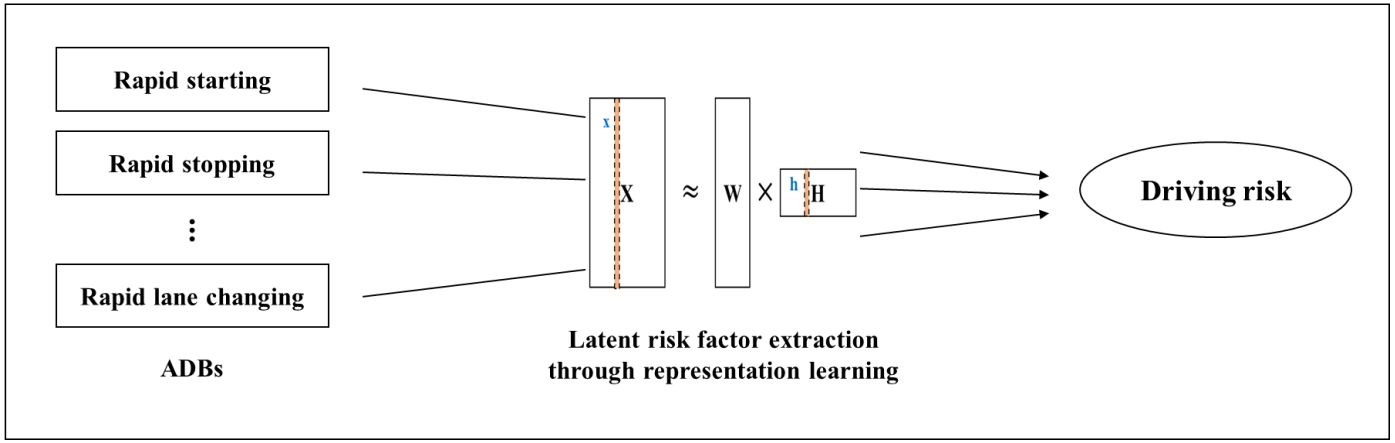


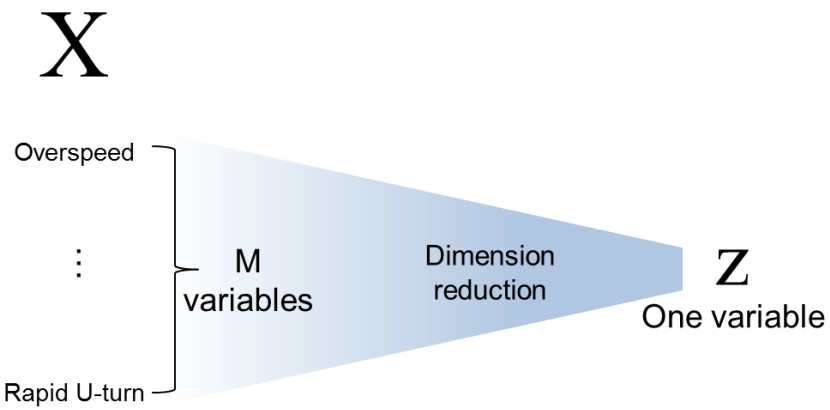
Driving Process Management: Safe Driving Context

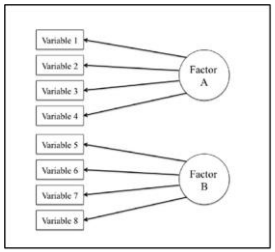


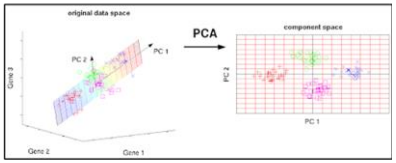
ADB	Bus criteria
Short-term over-speeding	The speed is 20 km/h above the speed limit
Long-term over-speeding	The speed is 20 km/h above the speed limit for 3 min
Rapid acceleration	The acceleration is greater than 6 km/h/s at a speed greater than 6 km/h
Rapid starting	The acceleration is greater than 8 km/h/s at a speed less than 5 km/h
Rapid deceleration	The deceleration is greater than 9 km/h/s at a speed greater than 6 km/h
Rapid stopping	The deceleration is greater than 9 km/h/s at a speed less than 5 km/h
Rapid lane changing	The change in rotation angle is 8°/s at a speed greater than 30 km/h, an acceleration (a deceleration) less than ±2 km/h/s, and an accumulated yaw rate change less than ±2°/s for 5 s
Rapid overtaking	The change in rotation angle is greater than 8°/s at a speed greater than 30 km/h, an acceleration greater than 3 km/h/s, and an accumulated yaw rate change less than ±2°/s for 5 s
Rapid turning	The accumulated change in rotation angle is from 60° to 120° (left or right) for 4 s at a speed greater than 20 km/h
Rapid U-turning	The accumulated change in rotation angle is from 160° to 180° (left or right) for 8 s at a speed greater than 15 km/h

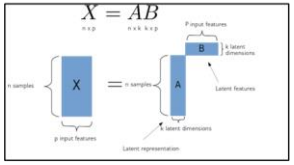
Driving Process Management: Safe Driving Context

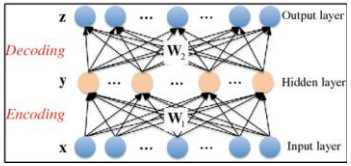




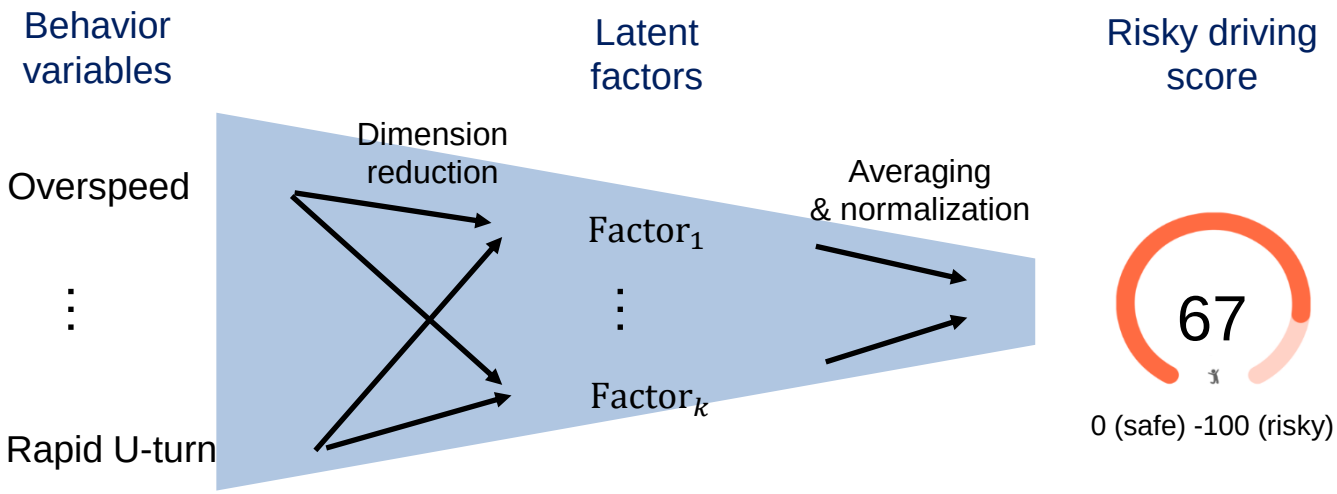


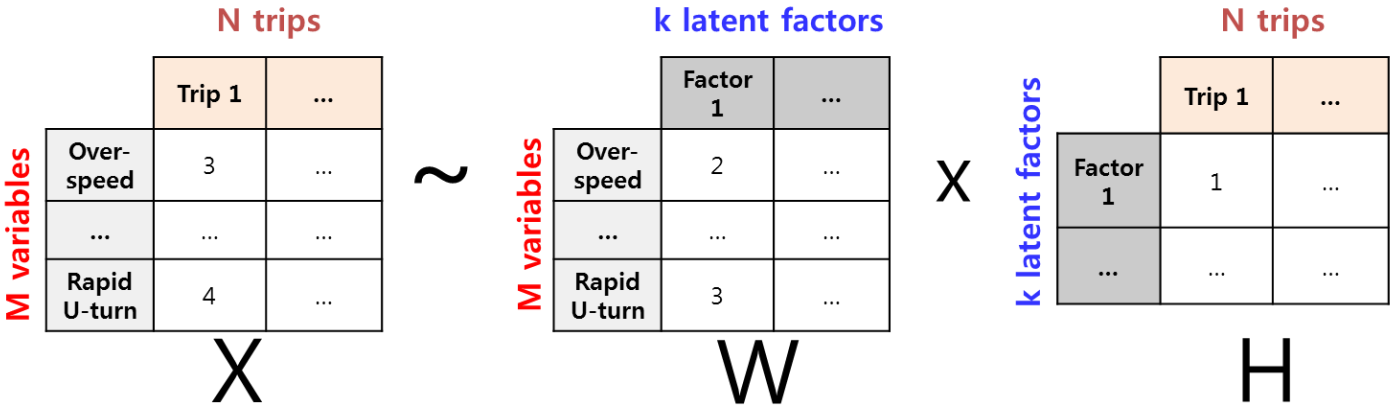




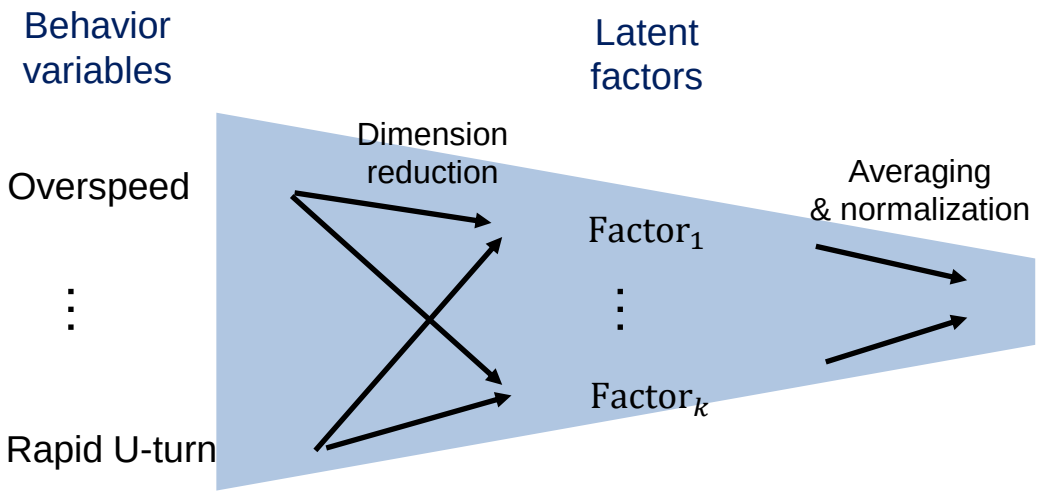


Driving Process Management: Safe Driving Context





Driving Process Management: Safe Driving Context



	Trip 1	...
Overspeed	3	...
Rapid stopping	5	...
Rapid U-turn	4	...

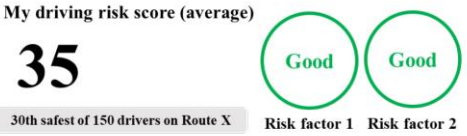
	Trip 1	...
Factor 1	1	...
Factor 2	2.5	...

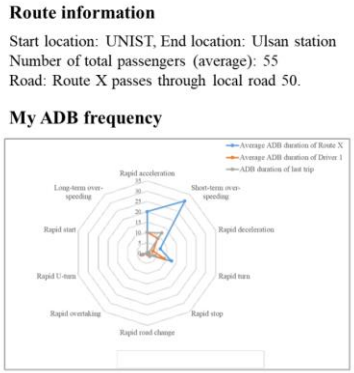
	Trip 1	...
Score	67	...

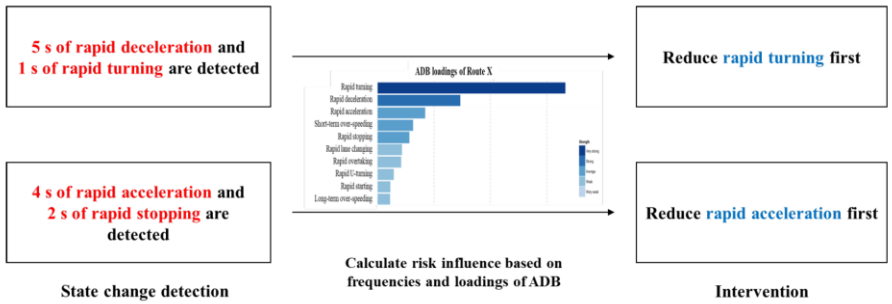
Driving Process Management: Safe Driving Context

LOADINGS OF 10 ADBS ON LATENT RISK FACTORS

Route number	Latent risk factors	Rapid acceleration	Short-term over-speeding	Rapid deceleration	Rapid turning	Rapid stopping	Rapid lane changing	Rapid overtaking	Rapid U-turning	Rapid starting	Long-term over-speeding
A	1	3,157.4	15,836.4	243.8	1,393.9	0.7372	0.8259	0.0001	5.8394	0	0
B	1	355.85	11.414	382.44	2,468.4	21.530	75.958	0	129.78	0	0
	2	242.01	7.5884	263.45	228.97	15.245	42.860	0.0368	86.534	0	0
C	1	5,697.7	0.0004	917.76	1,241.2	18.138	16.452	0.4746	57.896	0	0
	2	733.55	0	547.32	378.12	10.072	2.5321	8.0187	5.2734	0	0
	3	852.56	0.0003	331.79	943.05	49.444	11.642	7.9346	29.365	0	0

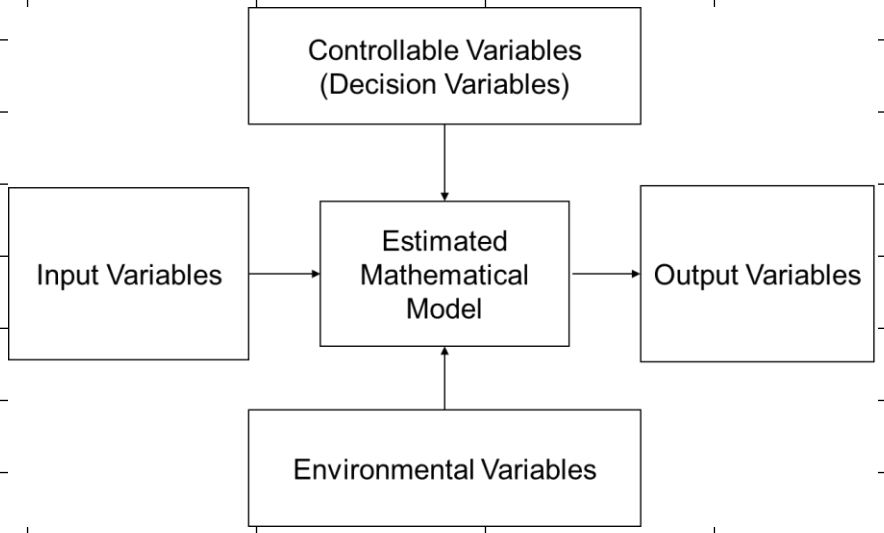






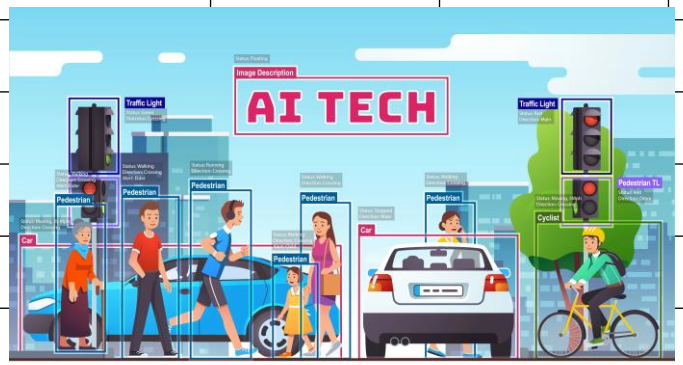
Behavioral Data for Personal Process Management

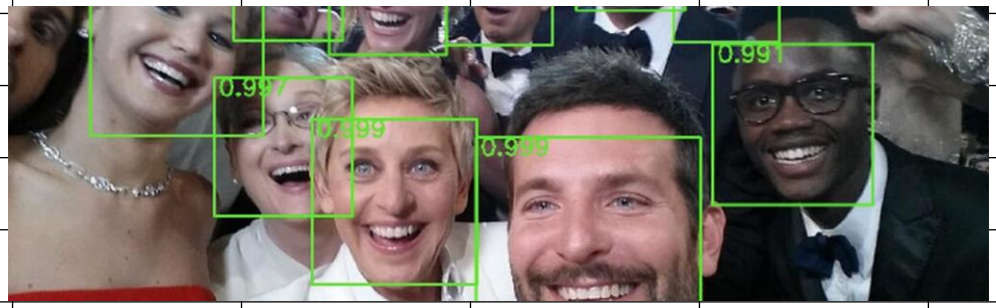
	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2	…					…
Customer 3	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…					…
…	…	…	…	…	…	…
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…



Behavioral Data for Personal Process Management

	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2						
Customer 3						
…						
…						
…						
…	…	…	…	…	…	…
…	…					…
…	…					…
…	…					…
Customer n-1	…					…
Customer n	…	…	…	…	…	…





Existence vs. Nonexistence of the Labels

	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2						
Customer 3						
…						
…						
…						
…						
…						
…						
…						
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…

Input Data
(Pre-processed)

Data \ Type	Variable (x_t)	Time window
Behavior data	Behavior 1	$S1_t, S1_{t-1}, \ldots$
	Behavior 2	$S2_t, S2_{t-1}, \ldots$
	…	$S3_t, S3_{t-1}, \ldots$
	Behavior 1	$Sk_t, Sk_{t-1}, \ldots$
	Data smoothing	
	$Mean(\sum_{i=0}^{n} x_{t-i})$	

Model

$$y = f(\mathbf{x}, \boldsymbol{\theta}) + \varepsilon$$

neural networks

Nonlinearity consideration

Decision trees

Rule-based explanation

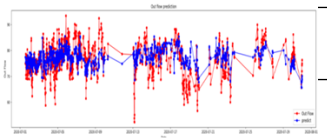
Regression

Linear coefficient estimation

Result

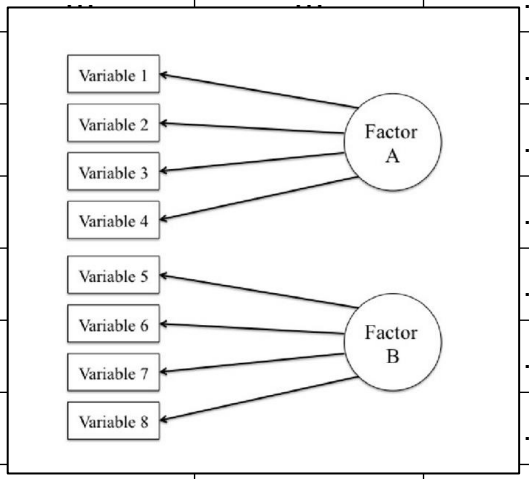
$$\hat{y}(\mathbf{x})$$

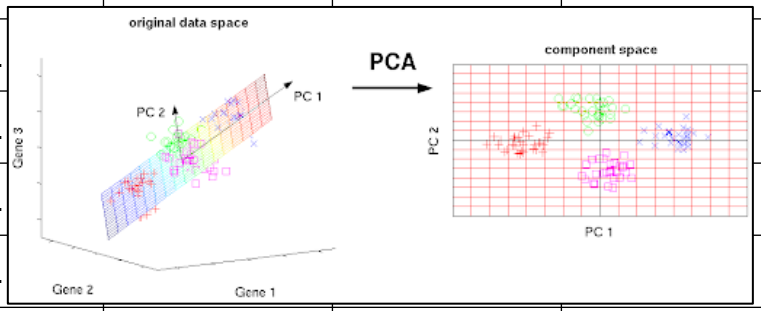
Behavioral outcomes

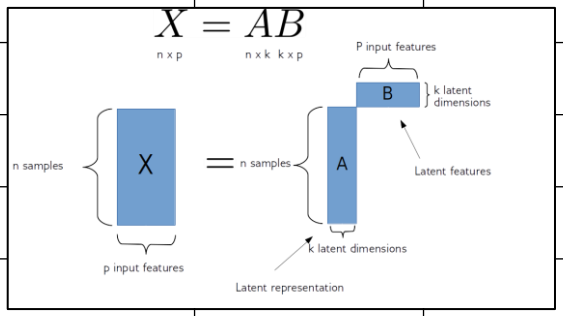


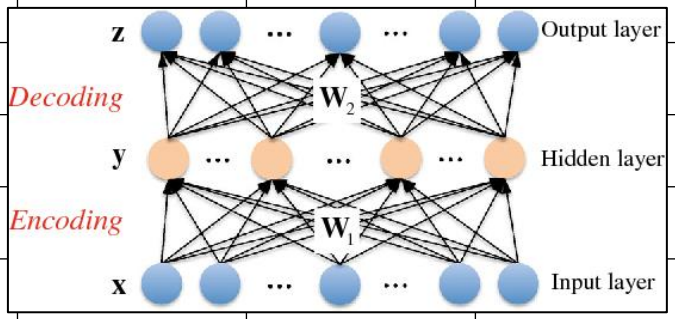
Existence vs. Nonexistence of the Labels

	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2			…	…	…	…
Customer 3			…			
…			…			
…			…			
…			…			
…			…	…	…	…
…						
…						
…						
Customer n-1						
Customer n						



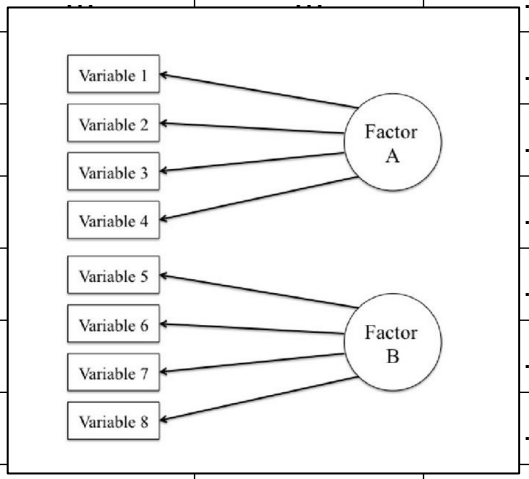


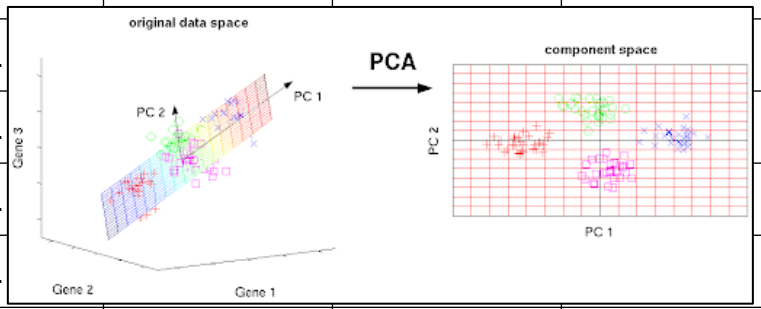


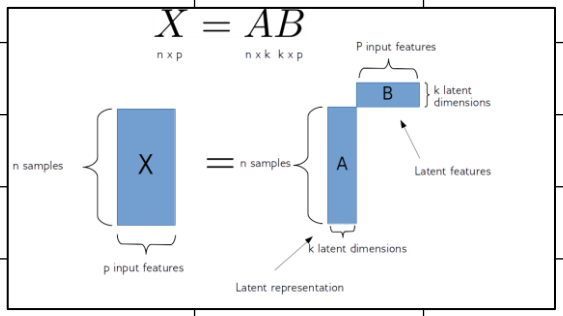


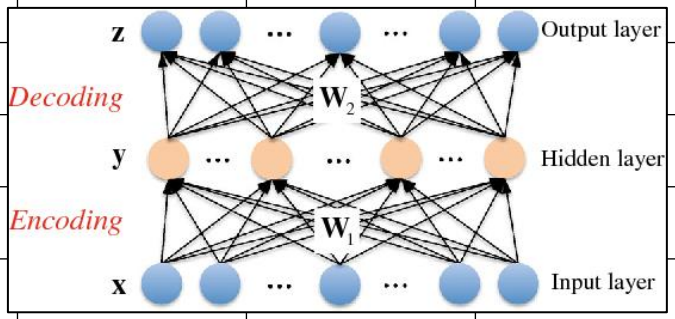
How Can We Validate the Case of Nonexistence of the Labels?

	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2			…	…	…	…
Customer 3			…			
…			…			
…			…			
…			…			
…			…	…	…	…
…						
…						
…						
Customer n-1						
Customer n						





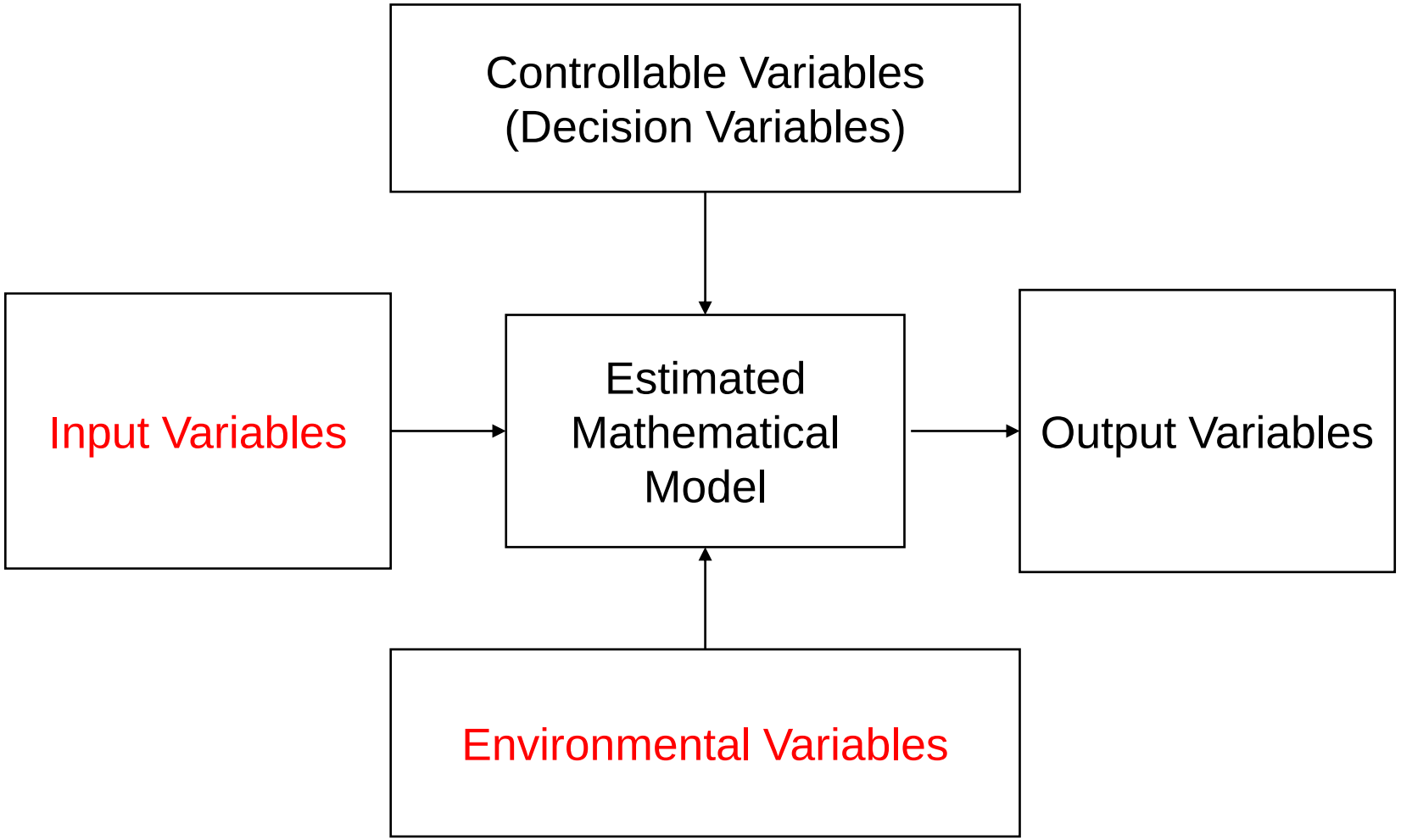




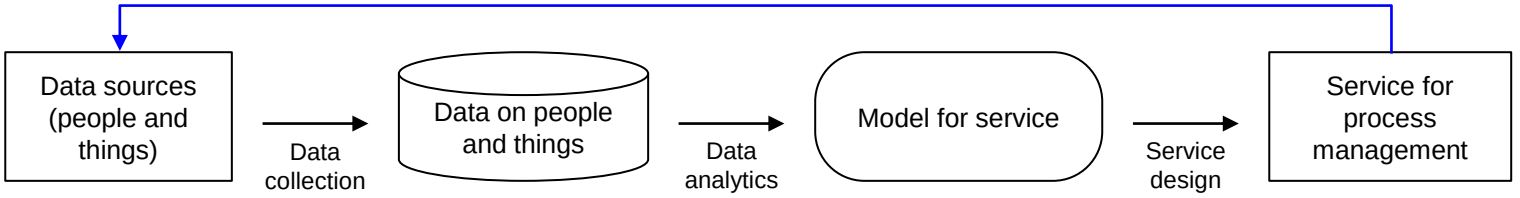
How Can We Address the Case of Existence of Few Labels?

	Behavioral feature 1	Behavioral feature 2	Behavioral feature 3	…	Behavioral feature m	Outcome label
Customer 1	…	…	…	…	…	…
Customer 2	…	…	…	…	…	…
Customer 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…

How Can We Address Consider the Input and Environmental Variations?



Personal Process Management: Challenges



Collecting the right data for service

Facilitating easy and spontaneous data collection from people and objects

Managing the quality of data for service

Planning data analytics for service

Integrating different data from various sources for service

Following the regulations on data usage

Protecting the customer privacy in using their data

Identifying the information useful to customers

Promoting incentives for customers to accept new information

Designing an effective and efficient data-based service delivery process

Mediating the different stakes of data-related stakeholders for service

Reference: Lim, C., Kim, M., Kim, K., Kim, K. and Maglio, P., "Using Data to Advance Service: Managerial Issues and Theoretical Implications from Action Research," *Journal of Service Theory and Practice*, Vol. 28, No. 1, 99-128, 2018.

Assignment 5 (by 10.23 11:59 pm)

- Based on the practice demonstration from TA Jung, (1) complete the construction of the behavior feature – outcome label matrix in the context of eco-driving by yourself. You should select significant behavior features (variables) based on your own descriptive analysis and eco-driving domain knowledge study.
- Then, (2) using the behavior feature – outcome label matrix you constructed, develop an eco driving score prediction model. Do it all by yourself, and describe the analysis process and outcome in detail. Interpret the outcome (e.g., describe the behavior features you identified significant, interpret the coefficient/importance values of behavior features to the FPK label).
- (3) Assume you need to use your machine for real-world driving support service (e.g., T map service or Hyundai blueLink service). How can you improve your machine to be used for the service effectively? For example, what kinds of data should you collect and use further to develop a complete driving support service? How would you design a method for using/learning the data? Think beyond these examples in your own creative, unique way!
- (4) You must have your own interested or favorite service WITHOUT a machine for data-driven personal process management (e.g., traditional services that do utilize customers' behavioral data yet). Discuss the requirements of personal process management for the service in detail.
- (5) If you would conduct a study on developing a machine for data-driven personal process management for the service, how would you conduct the research in your own creative, unique way? What kinds of data are you going to collect, analyze, and learn, and what methods are you going to use? Describe your service intelligence development plan in detail. If possible, visualize your plan clearly (e.g., draw an image, construct a mathematical model). To facilitate your thinking, you may want to identify and review a paper related to the service you are interested or concerned.
- Upload your code and a several paragraph essay on the tasks (1)~(5) in the Blackboard.

Eco-driving Practice Demonstration from TA Jung

2022.10.12. Wednesday

There is no class on 10.10. Monday