What is the future trend of decision making?

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Agenda

- Introduction
- Challenges
- Solutions
- Future trend
- Q&A

Introduction – Decision making models/tools

- Intelligent
- Consistent
- Adaptive
- Efficient and effective
- Limited usage in some domains (e.g. marketing)
- Why?

An example – Marking an essay

- Do you want to apply a model/tool to help marking an essay?
- Why?
- What are your concerns?
- What is/are the trade-off(s)?

Topic: How to improve the quality of teaching and learning?

Lodish (2001)

- Improvement cannot be always made when using the models:
  - *The model is used when not ready*
  - *The model is not used when ready*
  - *The managers may not use the model's results to improve his/her decisions*
  - *The decisions may not improve productivity even if the manager uses the model's results*

Lodish, Leonard M. (2001). Building marketing models that make money. Interfaces, 31(3), S45-S55.

Lodish (2001)

- “The most ***complex***, most ***complicated***, or more ***elegant*** model is not necessarily the model that will affect an organization and contribute to productivity.”
- “That model is much more likely to be the one that is ***most meaningful*** to the people who make decisions using a model as an aid.”

Little (2004)

- **Obstacles** to the use of models:
  - *Good models were hard to find*
  - *Good empirical estimation of parameters was even harder*
  - *Managers didn't understand the models*
  - *Most models were incomplete on critical issues*

Little, John D.C. (2004). Comments on "Models and Managers: the concept of a decision calculus": Managerial models for practice. Management Science, 50(12), 1854-1860.

Fisher (2004)

- "I have come to the conclusion that models can be deployed in one of two ways – either ***fully automated,*** untouched by human hands, or as a ***DSS*** under the direction of a manager."
- "I have found that these applications require a very accurate model and powerful optimization algorithms, but, after a validation phase, can be run as ***black boxes***."

Quoted in Little (2004).

Fisher (2004)

- "In the second mode, I have found that ***simplicity*** and ***transparency*** beats complex optimization every time because it enables a better coupling with the heavily involved manager."
- "Most of my ***failures*** have come from trying to deploy sophisticated, black box optimization models…because the managers…were unwilling to implement recommendations ***they didn't understand***."

Lilien (2011)

- Reasons for **lack of adoption**:
  - *Mental models are often good enough*
  - *Models do not solve problems; people do*
  - *Managers do not observe the opportunity costs of their decisions*
  - *Models require precision and analysis, while managers often prefer ambiguity and intuition*

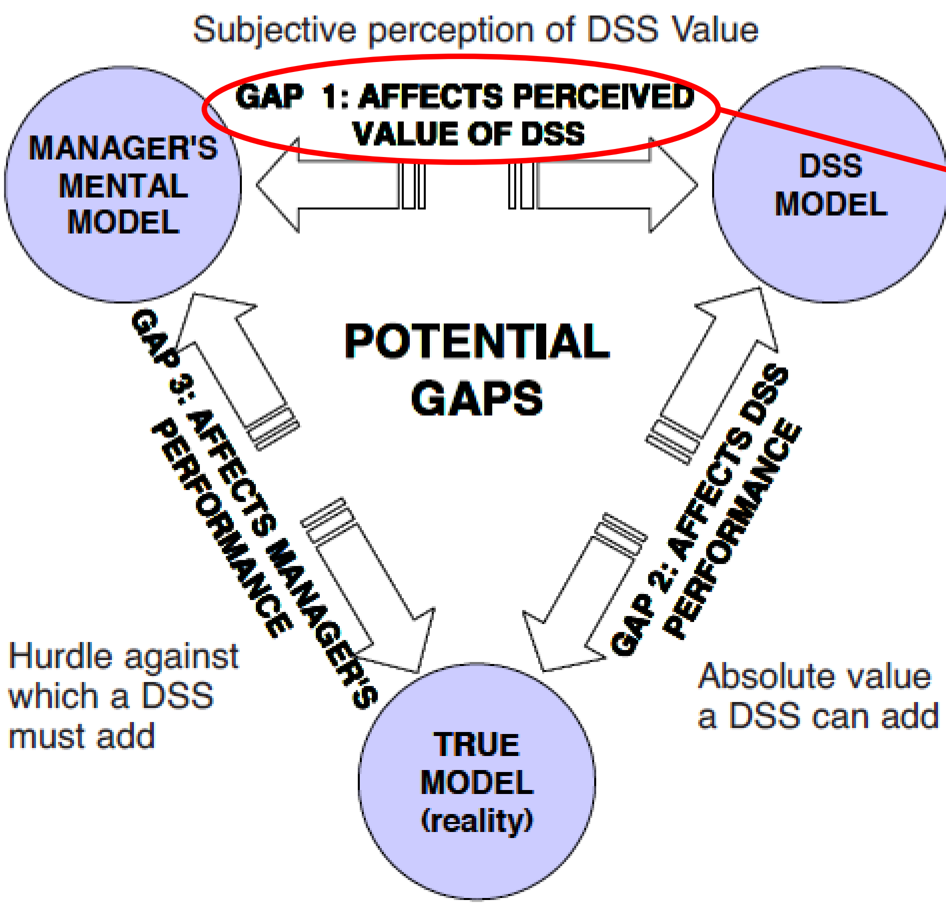
Lilien, Gary L. (2011). Bridging the academic-practitioner divide in marketing decision models. Journal of Marketing, 75, 196-210.

Solutions

- A set of guidelines for building models by Little (1970) ➔ Criteria for decision calculus:
  - *Simple*
  - *Robust*
  - *Easy to control*
  - *Adaptive*
  - *Complete on important issues*
  - *Easy to communicate with*

Little, John D.C. (1970). Models and managers: the concept of a decision calculus. Management Science, 16(8), B466-B486.

The Effect of Gaps Between Mental Model, DSS Model, and True Model



Notes: Relative actual value of a DSS = Gap 2 – Gap 3. Relative perceived value of a DSS = Gap 1.
Source: Kayande et al. (2009).

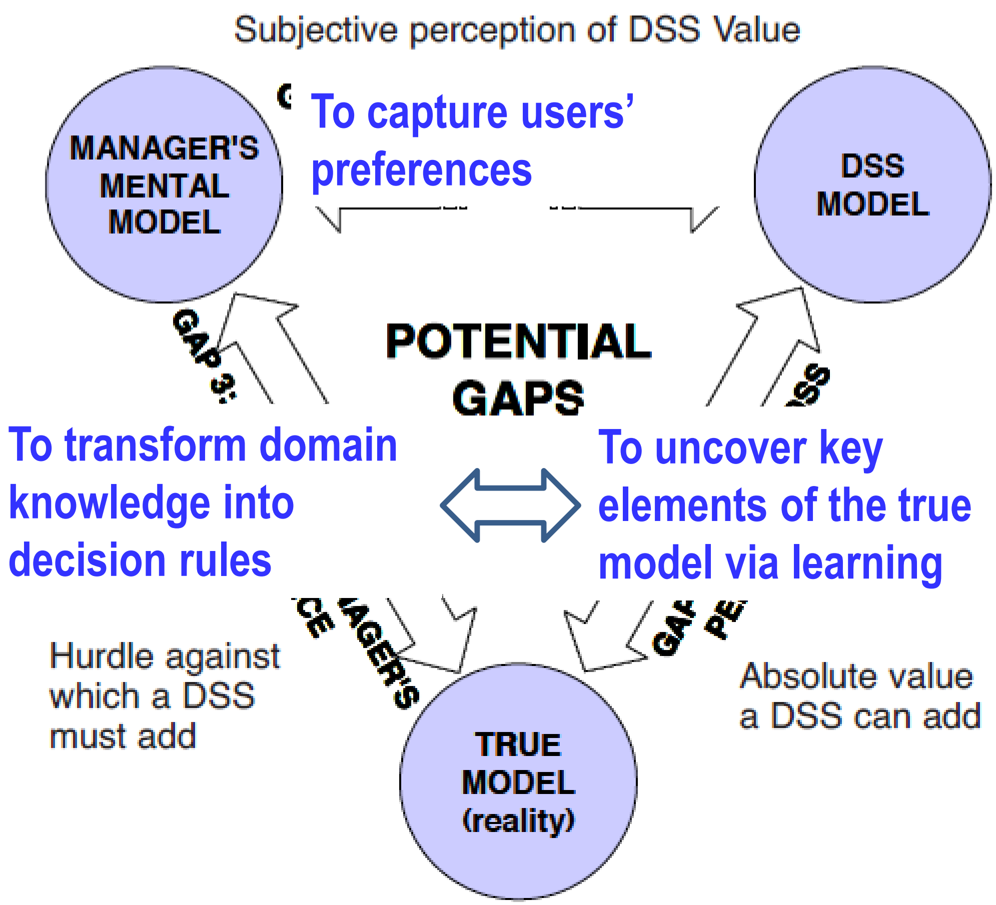
ons

"The model is often not designed to help users ***understand*** and ***internalize*** the underlying factors driving the model results and related recommendations."

Kayande et al. (2009) show that "a good model must provide ***feedback*** on upside potential as well as ***feedback*** on why and how to change."

Kayande, U., Arnaud De Bruyn, Lilien, Gary L., Rangaswamy, A., Van Bruggen G.H. (2009). How incorporating feedback mechanisms in a DSS affects DSS evaluations. Information Systems Research, 20(4), 527-546.

The Effect of Gaps Between Mental Model, DSS Model, and True Model



Notes: Relative actual value of a DSS = Gap 2 – Gap 3. Relative perceived value of a DSS = Gap 1.
Source: Kayande et al. (2009).

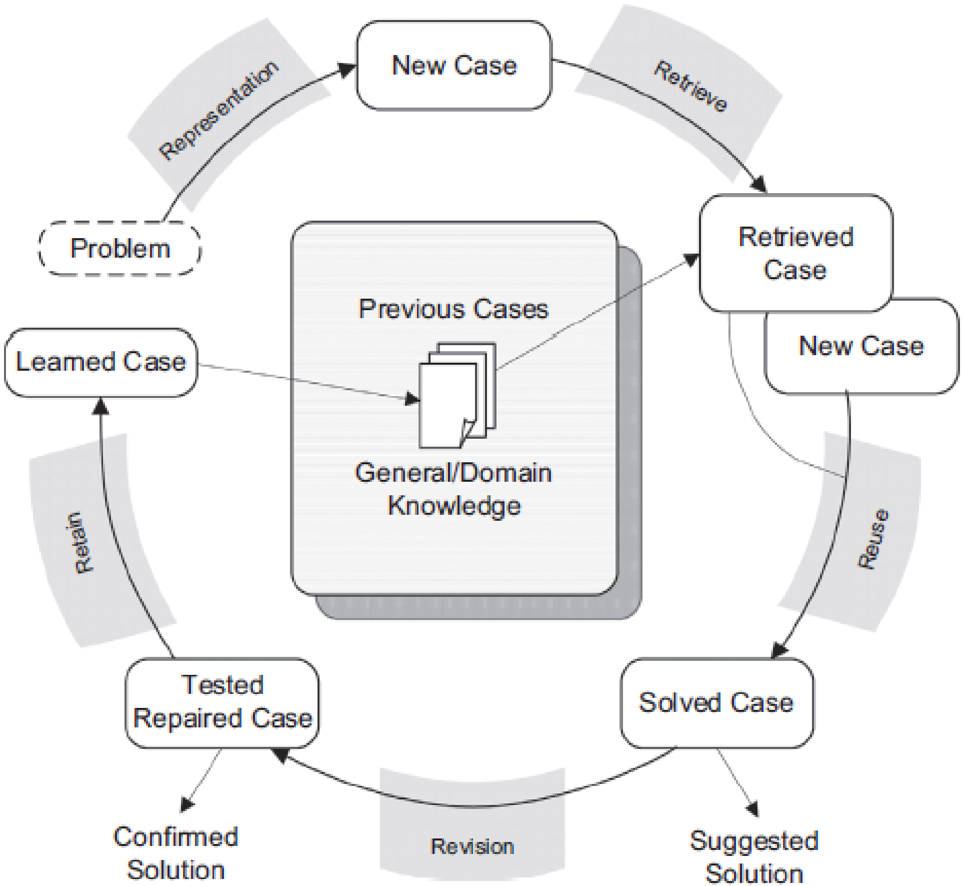
To transform domain knowledge into decision rules

Two main types of knowledge:

1. **Procedural** (know-how)
   - It is the knowledge exercised in the accomplishment of a task (formed by doing)
2. **Declarative**
   - It is the knowledge that can be expressed in declarative sentences or indicative propositions

- For example: Driving a car

To transform domain knowledge into decision rules



Case-based reasoning (CBR) is to **emulate** human reasoning for solving new problems (or making new decisions) by **remembering** past experiences.

Each case encloses the problem **description** and its associated **solution**. **E.g. C=F(A,B).**

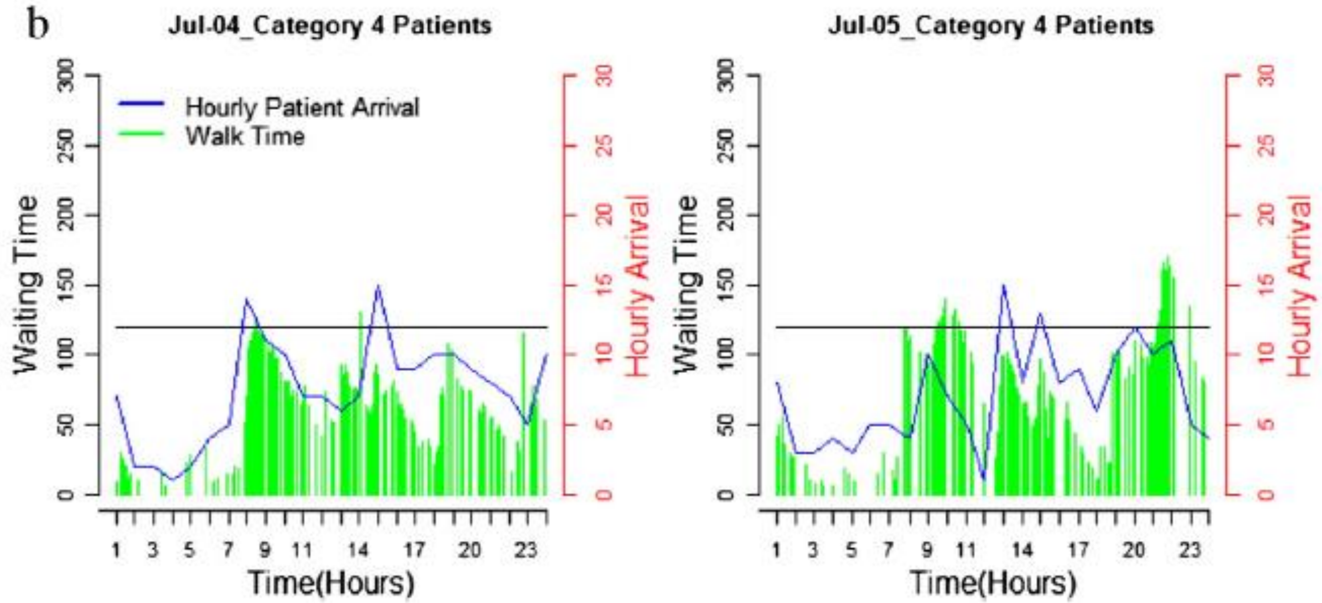
Roldan Reyes, E., Negny, S., Cortes Robles, G., and Le Lann, J.M. (2015). Improvement of online adaption knowledge acquisition and reuse in case-based reasoning: application to process engineering design. Engineering Applications of Artificial Intelligence, 41, 1-16.

To uncover key elements of the true model via learning

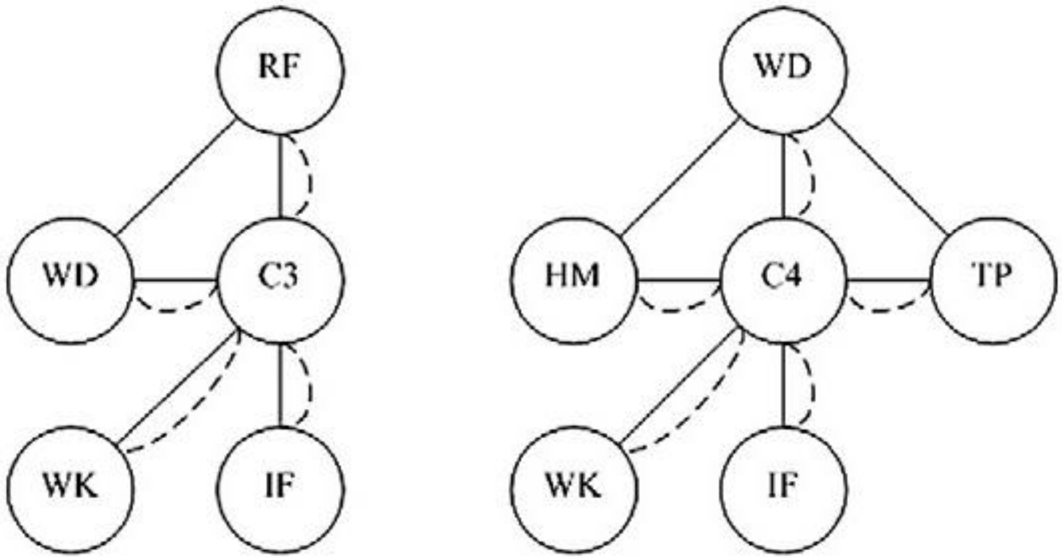
- ***Operational data*** need to be collected
- Statistical methods can be used to identify the ***associations*** between elements
- AI techniques can then be used to address the ***key elements*** in a quantitative manner
- For example:
  – Xu et al. (2013)
  – Wong and Chan (2015)

Xu et al. (2013)

- Identify the ***contributing variables*** to patient arrivals in a local emergency department and examine their ***associations***

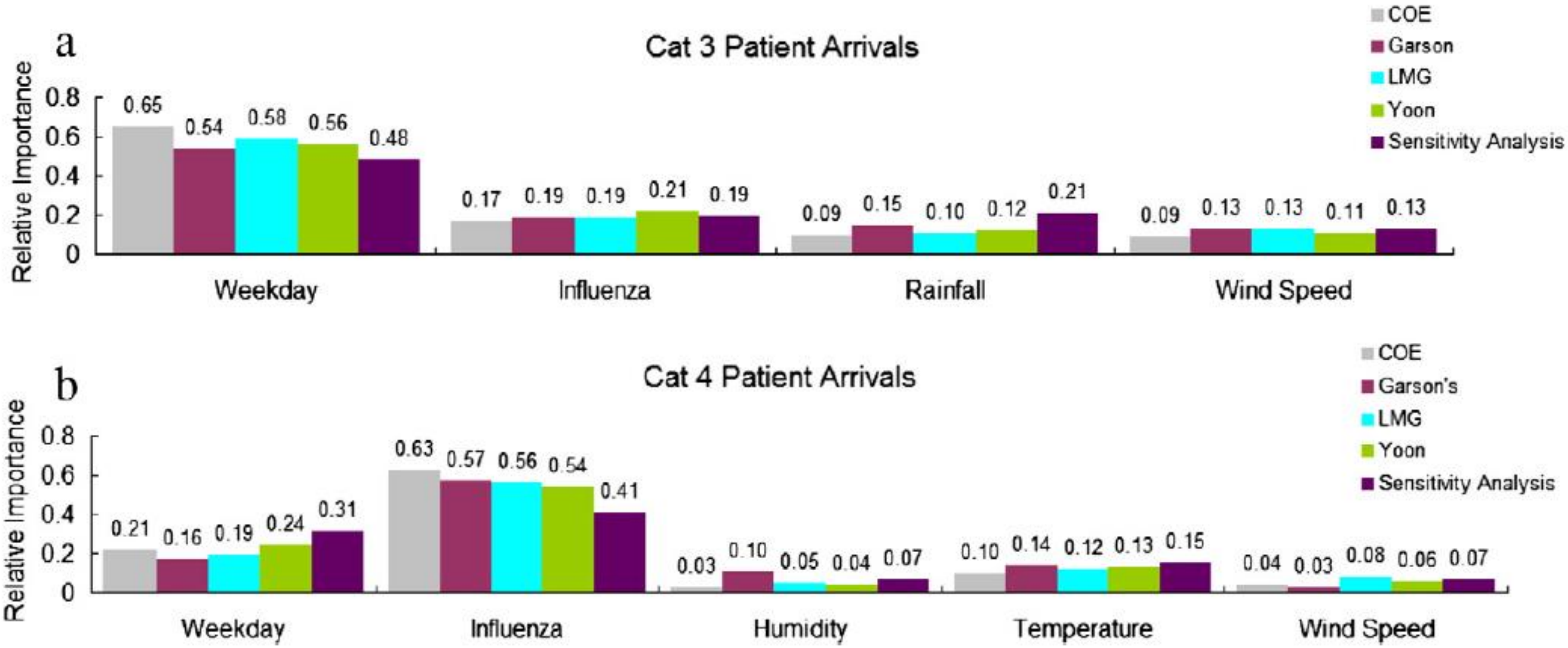


Xu et al. (2013)



Three different methods were used: **ANN, MLR and NLLSR**. Based on comparison results, ANN was deemed more reliable than MLR and NLLSR. The relative influence among factors was computed using ANN and MLR.

Xu et al. (2013)



a
Cat 3 Patient Arrivals
COE
Garson
LMG
Yoon
Sensitivity Analysis
Relative Importance
0.8
0.6
0.4
0.2
0
0.65 0.54 0.58 0.56 0.48
0.17 0.19 0.19 0.21 0.19
0.09 0.15 0.10 0.12 0.21
0.09 0.13 0.13 0.11 0.13
Weekday
Influenza
Rainfall
Wind Speed
b
Cat 4 Patient Arrivals
COE
Garson's
LMG
Yoon
Sensitivity Analysis
Relative Importance
0.8
0.6
0.4
0.2
0
0.21 0.16 0.19 0.24 0.31
0.63 0.57 0.56 0.54 0.41
0.03 0.10 0.05 0.04 0.07
0.10 0.14 0.12 0.13 0.15
0.04 0.03 0.08 0.06 0.07
Weekday
Influenza
Humidity
Temperature
Wind Speed

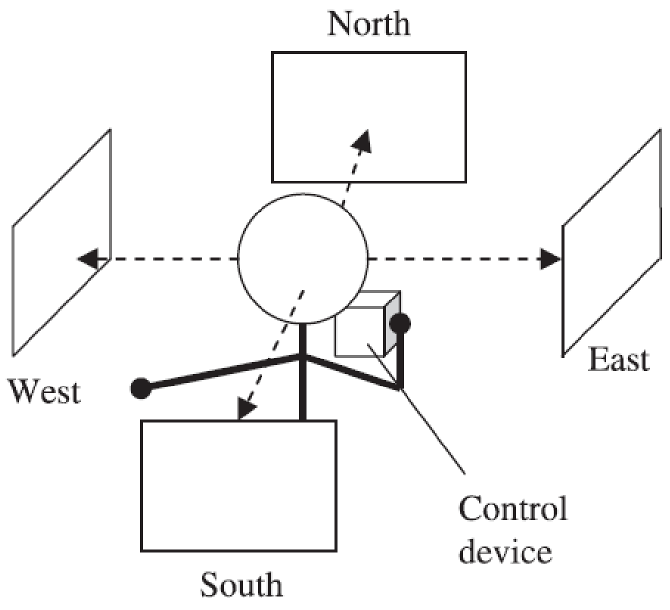
Xu et al. (2013)

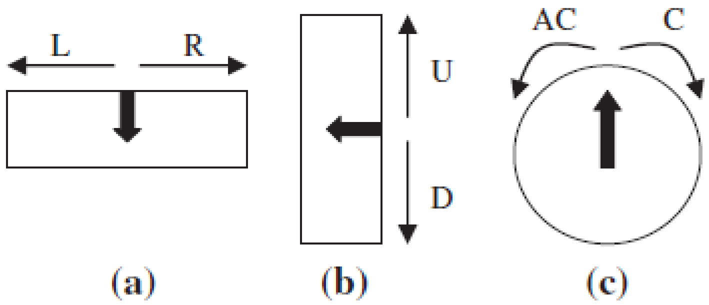
- Major findings:
  - Arrival of ***C3 patients*** was more sensitive to ***weekday*** and ***the effect of influenza***, and less sensitive to rainfall and wind speed. Temperature and humidity were found having no significant impact.
  - Arrival of ***C4 patients*** was sensitive to ***the effect of influenza*** and ***weekday***, and less sensitive to temperature, humidity and wind speed. The impact of rainfall was found insignificant.

Xu, M., Wong, T.C. and Chin, K.S. (2013). Modeling daily patient arrivals at emergency department and quantifying the relative importance of contributing variables using ANN. Decision Support Systems, 54, 1488-1498.

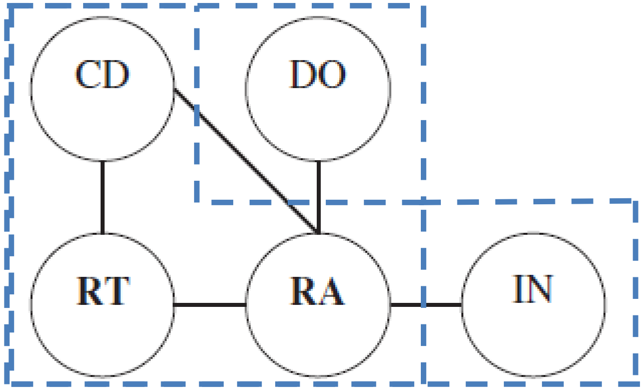
Wong and Chan (2015)

- Examine the ***association*** between the design variables and the users' performance



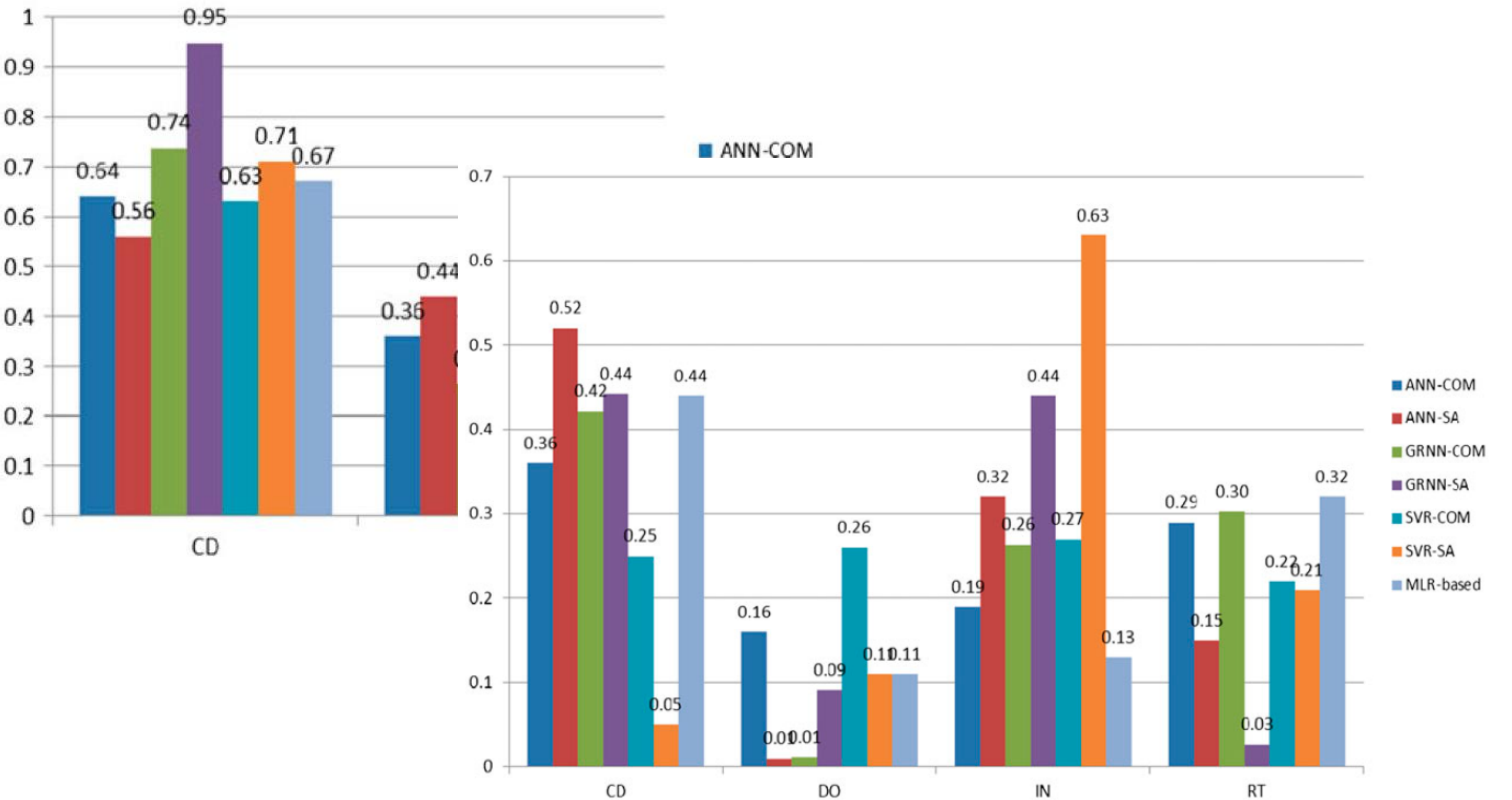


Wong and Chan (2015)



Five different methods were used: **ANN, GRNN, SVR, MLR and RSM**. Based on comparison results, ANN, GRNN, and SVR were deemed more reliable than MLR and RSM. The relative influence among factors was computed using ANN, GRNN, SVR, and MLR.

Wong and Chan (2015)

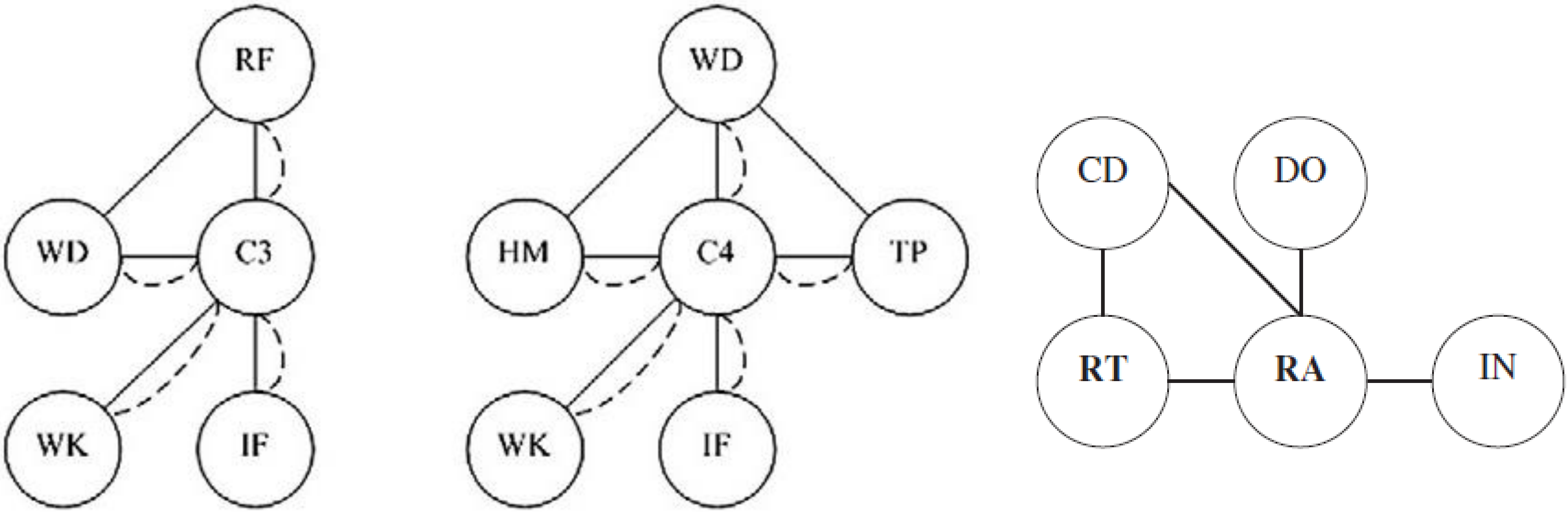


Wong and Chan (2015)

- Major findings:
  - To minimize ***RT***, a 2-way ***horizontal*** lever joystick must be used to execute the instructions which consists of L, R, U, D, C and AC motions with displays oriented in the four cardinal directions.
  - To maximize ***RA***, (1) a ***rotary*** or ***horizontal*** device must be used; and (2) both ***U*** and ***D instructions*** must be avoided where the C instruction is a marginal case.

Wong, T.C. and Chan, Alan H.S. (2015). A neural network-based methodology of quantifying the association between the design variables and the users' performances. International Journal of Production Research, 53(13), 4050-4067.

To uncover key elements of the true model via learning



The models can be more robust in identifying key factors and measuring their associations once more data can be collected over time, i.e. the process of "**learning**".

To capture users' preferences

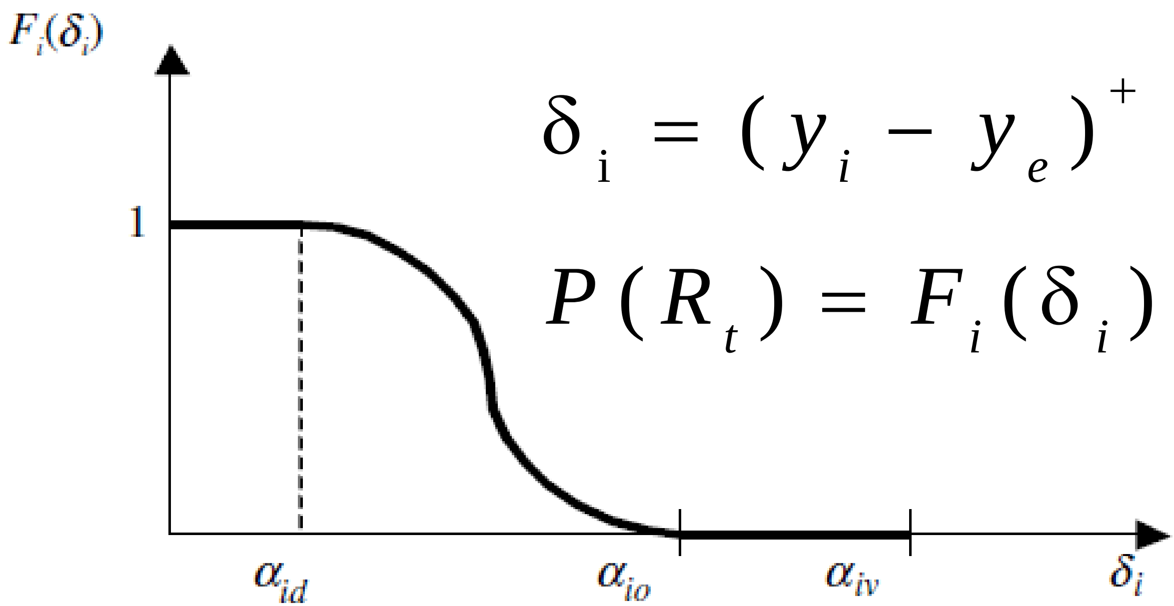
- To minimize ***gap 1*** (between mental and DSS models), users' preferences need to be examined
- Consider at time t:

$$R_t : y_i = F(w_1 x_1, w_2 x_2, \ldots, w_j x_j, \ldots w_n x_n)$$

- There are two ways to incorporate the preferences of decision makers into the DSS model:
  - ***Satisfaction functions***
  - ***Utility functions***

To capture users' preferences

- **Satisfaction functions** can be used to denote how the outcome (y_i) would meet the user's expectation (y_e)



$$\delta_i = (y_i - y_e)^+$$

$$P(R_t) = F_i(\delta_i)$$

Aouni, B., Ben Abdelaziz, F., and Martel, J.M. (2005). Decision-maker's preferences modeling in the stochastic goal programming. European Journal of Operational Research, 162. 610-618.

To capture users' preferences

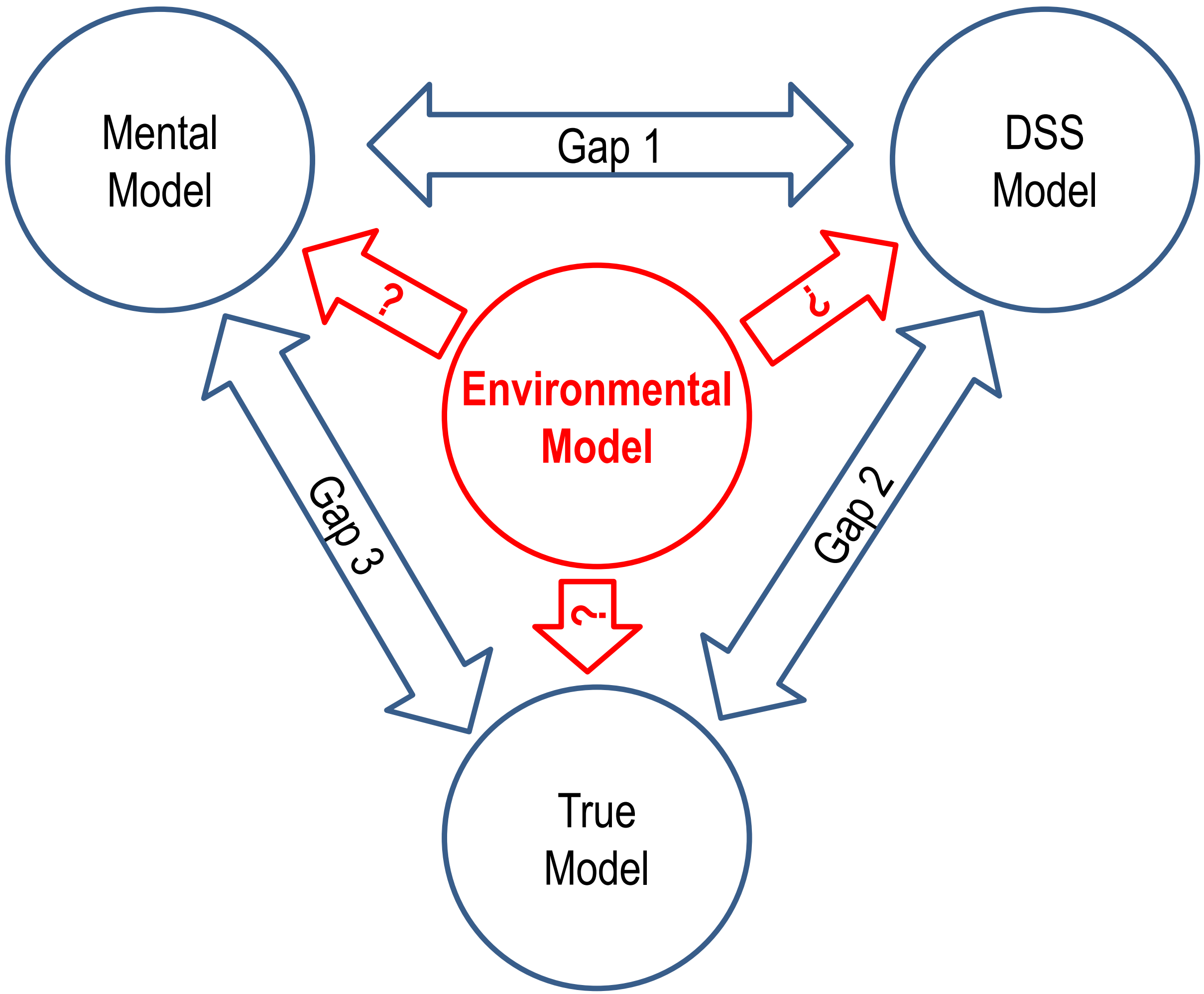
- **Utility functions** can be used to denote the weighted linear combination of the factors

- By the DSS model: $U_t = \sum_{j=1}^{n} w_j x_j$

- By the user k: $U_t^k = \sum_{j=1}^{n} w_j^k x_j$

$$\left.\begin{array}{l} U_t = \sum_{j=1}^{n} w_j x_j \\ U_t^k = \sum_{j=1}^{n} w_j^k x_j \end{array}\right\} P(R_t) = 1 - \frac{(U_t - U_t^k)^+}{U_t + U_t^k}$$

Future Trend?



Conclusion

- Challenges
  - *Gap 1 (between mental and DSS models)*
- Solutions
  - *Incorporation of users' preferences*
- Future trend
  - *The impact of environmental model*

Q&A

Thank you for your attention

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