

A Decision-based Design Framework for a Commercial Product

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Abstract

The purpose of this paper is to demonstrate the application of Decision-Based Design (DBD) framework to a commercial product—a Foldable Hand Truck. This paper's new contributions to DBD framework are the application of discrete choice analysis (DCA) in DBD framework that greatly simplifies the task of customer survey, resembles the real purchase behavior of the customers and reflects their preferences on the product design better, and recommendations for the utilization of the DBD framework in future product design applications. The selected application problem is a Foldable Hand Truck. In contrast with the conventional hand truck, a foldable hand truck can be folded and moved through the stairs. Also, the feature foldability saves a considerable amount of storage space.

Keywords

Arrow's impossibility, decision-based design, engineering design, multi-criteria design approach

1. Introduction

The engineering design process is a series of steps that engineers follow when they are trying to solve a problem and design a solution for something (Tayal, 2013). According to the US Accreditation Board for Engineering and Technology (ABET), engineering design is defined as the process of devising a system, component, or process to meet desired needs. It is a *decision-making process* (often iterative), in which the basic science and mathematics and engineering sciences are applied to convert resources optimally to meet a stated objective (Tayal, 2013). The establishment of objectives and criteria, synthesis, analysis, construction, testing, and evaluation are among the fundamental elements of the design process (Chen et al., 2012).

Two steps constitute the engineering design, which are: (1) determining the possible design options and (2) choosing the best one (Li and Azarm, 2000). These steps seem simple but the problem is, for most products, the range of possible design options is literally infinite. Also, there is no single universally accepted design process.

Traditional engineering design is conducted primarily with an engineering-centric viewpoint, with limited or no input from the other functional domains and thus establishing a one-way communication between different domains (Krishnan and Ulrich, 2001). Product development is carried out through a sequence of analysis, evaluation, modification, and refinement processes (Ohsuga, 1989). Thus customer preferences are ambiguously and incompletely incorporated in the engineering design specification resulting in sub-optimal solutions. Decision-Based Design (DBD) is an approach to engineering design that seeks to select an unambiguous design alternative from the available options by considering the inter-domain decisions so that the selected design maximizes the overall economic benefit of the organization.

Furthermore, traditional selection approaches use a variety of multi-criteria decision-making methodologies which, at times, can cause problems resulting in irrational choices during the alternative selection stage (Ben-Akiva and Lerman, 1985; Hazelrigg, 1998). Assignment of weights and multi-attribute ranking are two common approaches where decisions based on multiple-criteria are to be made. But weights and ratings are subjective in nature, i.e., they are dependent on the decision maker's intuition, experience, and judgment (Chen et al., 2012). Also, they often become manipulated by the decision-maker to get favorable results. For example, an attribute can be given unusually high weight if it is positively correlated with the product's success. In the case of multi-attribute ranking,

the selection result is more dependent on the method of ranking rather than the underlying qualities of the alternatives (Saari, 2000). Furthermore, multiple-criteria decision making can often lead to Arrow's impossibility- a concept which basically says that group consisting of rational individuals does not always exhibit rational preferences when choosing over multiple alternatives (Arrow and Raynaud, 1986; Wassenaar et al., 2005). Hazelrigg illustrated it with a simple example that Arrow's impossibility can occur during engineering design resulting in sub-optimal decisions (Hazelrigg, 1995, 1999). Hazelrigg also illustrated that Quality Function Deployment (QFD) - a popular multi-criteria approach to alternative selection can produce inconsistent results according to Arrow's Impossibility Theorem (Hazelrigg, 2003). Moreover, multi-criteria approaches involve customer surveys where the customer has to actively rank, rate or evaluate a number of product alternatives which can be tiring. It can be avoided by DBD since it involves DCA where the respondent's task is simply to choose which product to buy. This greatly simplifies the survey procedures and is very convenient for the customers (Wassenaar and Chen, 2003). How DBD tackles these difficulties by using a single-criterion approach instead of a multi-criteria approach has been described in this paper. The DBD framework has been illustrated by solving a new product design problem.

The rest of this paper is organized as follows. In Section 2, the DBD methodology- a single criterion design approach is explored in detail. DBD framework is applied to solve the foldable hand truck design problem in Section 3. Finally, in Section 4, a closure of this paper is given and the potential scope of future research on this topic is discussed by pointing out some limitations associated with the DBD methodology.

2. DBD Methodology

As an enhancement of Hazelrigg's (1998) framework, Wassenaar et al. (2003) proposed a DBD framework. This framework for single-loop optimization is different from using two separate loops for optimizing design options and the price in Hazelrigg's framework (Wassenaar and Chen, 2003). Also, it incorporates discrete choice analysis with logistic regression to better predict the demand or market share.

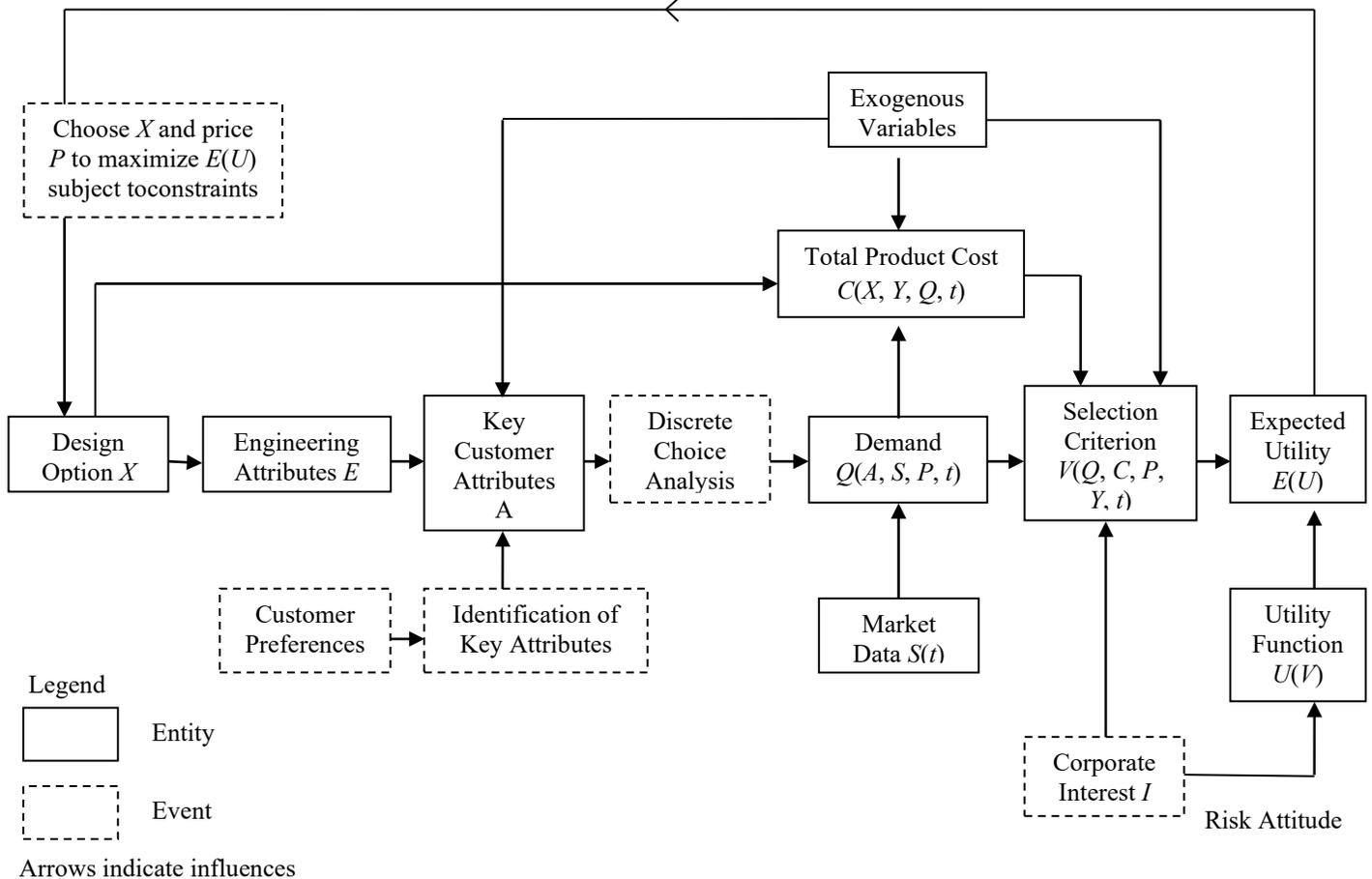


Fig.1 Decision-based design flowchart (Wassenaar and Chen, 2003)

2.1 DBD Flowchart

The flowchart of the DBD product selection process is shown in Fig. 1. The design options or the design variables are represented as X . The key customer attributes A are the product features based on which the customers evaluate the product when they make a purchase. Examples of such can be price, weight, strength, reliability, durability aesthetics, ease of use, product-specific features, etc. Identification of the key customer attributes from customer preferences is the first step of DBD framework. This can be done by analyzing customer behavior. The engineering attributes E represents the product properties that must be satisfied during its design. These are represented as functions of design variables X . Engineering attributes, in turn, establish an analytical relationship between the design options X and the key customer attributes A . The demand model Q is obtained from DCA by fitting the survey data using logistic regression. The single criterion here is profit V which is a function of demand (percentage market share), product cost C , price P and exogenous variables Y which represent uncertain factors. Market data S represents the characteristics of the market population such as age, gender, income, etc. The overall market population who are likely to use the product includes all the potential customers for the new product (which is being developed) as well as the competitor's current customers. The expected utility of the product is generally defined in monetary terms. Therefore, profit V equals the expected utility of the product. The corporate interests I may act as managerial constraint e.g., a specified minimum market share or a specified target profit. The time t is considered when profit V is discounted to the Net Present Value (NPV).

The goal is to select the design options X in such a way that they are consistent with the survey data of customer choices (which determine the predicted market share by DCA) and maximize the expected utility (profit) for the product simultaneously. This is obtained by establishing a loop, which iterates until the solution X converges resulting in optimal points for both customer preferences and expected utility. This can be simply illustrated by Fig. 2 as shown below.

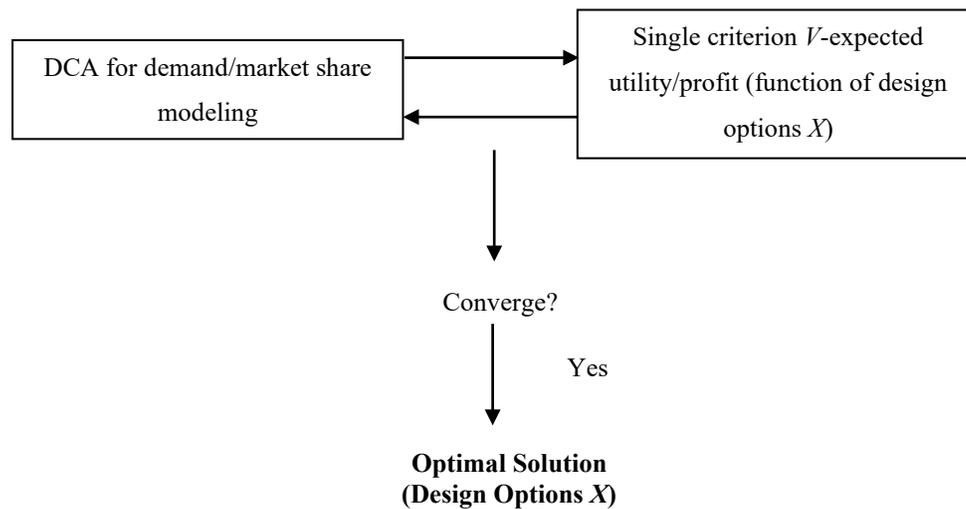


Fig. 2 DBD objective

2.2 Discrete Choice Analysis and Binary Logit Model

Discrete Choice Analysis (DCA) has been proposed as a major enhancement to the DBD framework. The DCA is used to predict the market share. The incorporation of DCA also greatly simplifies the task of customer survey resembling the real purchase behavior of the customers and reflecting their preferences on the product design.

The respondent's choice depends on product attributes, socioeconomic and demographic (respondent's own characteristics) attributes (Koppelman and Bhat, 2006). Respondent tends to select the option which tends to maximize his/her utility. For example, if there are two alternatives A and B , then the respondent's decision can be modeled as-

If, $U(A) > U(B) \rightarrow$ choose A

If, $U(A) < U(B) \rightarrow$ choose B

Where $U(A)$ and $U(B)$ denotes the measure of the utility of alternatives A and B , respectively (Ben-Akiva & Lerman, 1985).

Assuming linear relationship the utility functions can be modeled as-

$$U(A) = \beta_0 + \beta_1 \times P_{1A} + \beta_2 \times P_{2A} + \beta_3 \times D_1 + \dots \quad (1)$$

$$U(B) = \beta_4 + \beta_1 \times P_{1B} + \beta_2 \times P_{2B} + \beta_5 \times D_1 + \dots \quad (2)$$

Where,

P_{1A} = Measure of product attribute 1 for alternative A

P_{1B} = Measure of product attribute 1 for alternative B

D_1 = Measure of respondents own characteristics (e.g., gender, income, etc.)

The β coefficients of product alternatives are identical across the utility functions in which they apply since the utility value of a specific product attribute does not vary across the alternatives (Koppelman and Bhat, 2006). The outcome of the choice is binary in nature since the respondent either chooses a particular alternative or does not. The probability that alternative A is chosen over alternative B is the same as the probability that the n th customer utility of alternative A exceeds that of alternative B which can be expressed using the following equation:

$$\Pr_n(A) | [A, B] = \Pr_n(U(A) > U(B)) = \frac{e^{U_{An}}}{e^{U_{An}} + e^{U_{Bn}}} \quad (3)$$

The binary logit model can be extended to the multinomial logit model as expressed in Eq. (4). Here C_m represents the choice set with m competing products where $m \geq 2$.

$$\Pr_n(i) | [C_m] = \frac{e^{U_{in}}}{\sum_{l=1}^m e^{U_{ln}}} \quad (4)$$

Equation (4) can be read as the probability that the n th customer or respondent chooses alternative i from the given choice set of m . The choice probabilities for all customers of each individual competing product alternative can then be aggregated to estimate their demand and choice shares.

3. Numerical example

There is a wide variety of industrial applications of the DBD framework and it has already been applied in both mass production and large industrial projects like ship design. Chen et al. (2013) in the book titled "Decision-Based Design" presented two case studies- electric motor design and vehicle engine design problem where DBD has been applied. Application of DBD has been carried out by Mistree et al. on ship design problems (Mistree et al., 1990) and by Deepak et al., in automotive suspension system design problem (Kumar et al., 2006).

The DBD framework is applied to a product design problem. The intended product is a foldable hand-truck. Hand-truck is widely used in hospitals to carry medium loads and airports for carrying luggage and even in small industries for manual material handling purposes. The local market is dominated by a brand named Robustworks. Relative to Robustworks, our product's unique feature is that it can be moved through stairs but this feature has the penalty of weight and price to increase. The DBD framework will take this trade-off into account and come up with the best possible design options that are consistent with customer preferences and engineering constraints.



(a)



(b)

Fig. 3 Foldable Hand-Truck
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3.1 The product-Foldable Hand Truck

Rendered images of Computer-Aided Design (CAD) model of the product have been given in figure 3. Fig. 3(a) represents the folded position of the hand-truck, whereas Fig. 3(b) represents the unfolded position. The product has been designed and rendered in SolidWorks 2014.

3.2 Discrete Choice Analysis for Predicting Market Share

The choice sets for two proposed alternatives and one competitor are presented in Table 1.

Table 1: Choice sets

Key Customer Attributes	Alternative 1	Alternative 2	Robustworks (competitor)
Foldability (Yes/No)	Yes	Yes	Yes
Mass (kg)	9.5	9	8
Maximum Capacity (kg)	350	300	300
Stair Climbing Feature (Yes/No)	Yes	Yes	No
Price (BDT)	9500	9500	8000

15 individuals from different industries participated in the survey. Each individual was presented these choice sets and asked to choose the best option. Individuals were characterized by the extent of load they expect to carry that is either medium or heavy load user.

To deal with the categorical data we introduce categorical variables as follows:

1. Foldability, Yes = 1, No = 0;
2. Stair climbing feature, Yes = 1, No = 0;
3. User type, Heavy user = 1, Medium user = 0.

Although the feature foldability does not vary across the choices (and thus could be dropped), we include it anyway to examine its effect, i.e., we should get its β coefficient 0 (or close to 0) in the logistic regression.

3.3 Logistic Regression

The utility equations of alternative 1, alternative 2 and Robustworks are given as follows:

$$U_{Alt1} = \beta_0 + \beta_1 C + \beta_6 F_1 + \beta_7 M_1 + \beta_8 MaxC_1 + \beta_9 S_1 + \beta_{10} P_1 \quad (5)$$

$$U_{Alt2} = \beta_2 + \beta_3 C + \beta_6 F_2 + \beta_7 M_2 + \beta_8 MaxC_2 + \beta_9 S_2 + \beta_{10} P_2 \quad (6)$$

$$U_{Robustworks} = \beta_4 + \beta_5 C + \beta_6 F_3 + \beta_7 M_3 + \beta_8 MaxC_3 + \beta_9 S_3 + \beta_{10} P_3 \quad (7)$$

Table 2 shows the β coefficient estimates from the logistic regression.

Table 2: Results from logistic regression

β Coefficient	β Coefficient estimates
β_0	-3.79
β_1	12.47
β_2	5.56
β_3	-9.01
β_4	1.23
β_5	-0.457
β_6	1.85×10^{-7}
β_7	-4.02454536
β_8	1.760524958
β_9	2.767366958
β_{10}	1.345755031

As expected, β_6 has a value close to zero indicating that foldability has no effect on the utility equations. In Eq. (8), $\Pr_n(1)$ is the probability of respondent n choosing alternative 1 over alternative 2.

$$\Pr_n(1) | [1,2] = \frac{e^{U_{1n}}}{e^{U_{1n}} + e^{U_{2n}}} \quad (8)$$

In general format, it can be shown as

$$\Pr_n(i) | [C_m] = \frac{e^{U_{in}}}{\sum_{l=1}^m e^{U_{ln}}} \quad (9)$$

where C_m represents the choice set with m competing products.

Putting the values of β Coefficient in Eq. (8) and aggregating and dividing the choice probabilities for the 15 individuals the probabilities of choosing Alternative 1, Alternative 2 and Robustworks can be obtained as follows:

$$\Pr(\text{Alternative 1}) = 0.399$$

$$\Pr(\text{Alternative 2}) = 0.297$$

$$\Pr(\text{Robustworks}) = 0.304$$

Since Alternative 1 seems much more promising than Alternative 2, it is the preferred option. Dropping down Alternative 2, new probabilities can be obtained as:

$$\Pr(\text{Alternative 1}) = 0.57$$

$$\Pr(\text{Robustworks}) = 0.43$$

If the total market demand is forecasted as 20000 units per year, market share, $Q = 0.57 \times 20000 = 11400$ units.

3.4 Design options X

The design options X that can be related to the key customer attributes are given in Table 3. The ranges of the design options are chosen wide so that accidental exclusion of preferred design alternatives can be avoided.

Table 3: Proposed design options and their range

Design Options	Corresponding Symbols and Range	Nature of variables
Outside diameter of the tubular frame (mm)	$1.8 < D_0 < 3.0$	Continuous
Length of base (cm)	$90 < L < 110$	Continuous
Width of base (cm)	$34 < W < 51$	Continuous
Thickness of noseplate (mm)	$0.17 < T_{ns} < 0.30$	Continuous
Extension of noseplate (cm)	$24 < L_{ns} < 35$	Continuous

3.5 Engineering Analysis

The engineering analysis is intended to establish the functional relationship between the key customer attributes A and design options X .

Total mass of the body, M (kg) = Mass of base + Mass of noseplate + Mass of connecting rod + Constant mass =

$$5[(D_0 \times 10^{-2})^2 - (0.2 \times 10^{-2})^2] \times 10^{-2} \times L \rho + (WT_{ns} L_{ns} \rho \times 10^{-6}) + \pi \times [(10^{-2})^2 - (0.95 \times 10^{-2})^2] \times 10^{-2} \times W \times \rho + 4.50 \quad (10)$$

AISI 304 is used as body material, the density of which is, $\rho = 7960$ kg/m³.

The maximum capacity of the product depends on outside diameter of the tubes (D_0), length (L) and width (W) of the base. From SolidWorks Simulation for each applied load, corresponding values of these factors can be obtained. By fitting this dataset through linear regression, the equation of the maximum capacity can be obtained as-

$$C_{max} = -158.8 + 282.86 \times D_0 - 3.54 \times L + 6.68 \times W \quad (11)$$

3.6 Product cost modeling

Product cost analysis defines the relation between design option X and the total cost of the product. The total product cost C is based on design, material and labor cost. The total labor cost is assumed to be 25% of the total material cost. Table 4 summarized all these costs.

Table 4: Product costs

Type of Cost	Cost
Design cost	25,00,000
Labor cost	25% of the material cost (assumed)
Market price of AISI 304	180 BDT/kg

3.7 Problem description

Given,

Market size 20000 units/year

Key customer attributes A and Engineering attributes E

Find,

Design options X .

Maximize,

Profit $V = \text{Market share } (Q) \times \text{Selling price } (P) - \text{Total cost } (C)$ (profit =single criterion)

$$\text{Or, } V = 11400 \times 9500 - (2500000 + 1.25 \times (((5 \times [(D_0 \times 10^{-2})^2 - (0.2 \times 10^{-2})^2]) \times 10^{-2} \times L\rho + (WT_{ns} L_{ns} \rho \times 10^{-6}) + \pi \times [(10^{-2})^2 - (0.95 \times 10^{-2})^2] \times 10^{-2} \times W \times \rho + 4.50) \times 180) \times 11400 \quad (12)$$

Subject to,

Mass, $M = 9.5 \text{ kg}$ (13)

Maximum capacity, $C_{max} = 350 \text{ kg}$ (14)

Maximum capacity of noseplate, $C_{noseplate} \geq 100 \text{ kg}$ (15)

The algorithm of this optimization problem can be expressed as follows:

DBD Algorithm
Initial market share from DCA.
repeat
Optimization of the objective function (12) subject to constraints (13), (14) and (15)
Calculate new market share.
until convergence
return X

3.8 Results

The problem has been solved in MATLAB 2017 using the genetic algorithm optimization tool. The results are tabulated in Table 5. Final results show the dimension of the preferred design based on DBD framework. The sales are calculated by multiplying the yearly demand, market share and unit price. The calculation is done based on the currency of Bangladesh (Bangladeshi Taka or BDT).

Table 5: Results of the DBD Simulation

Preferred design options	Outside diameter of the tubular frame (mm)	2.2306
	Length of the base (cm)	99.9757
	Width of the base (cm)	34.5926
	Thickness of the noseplate (mm)	0.1946
	Extension of noseplate (cm)	24.3870
	Foldability (Yes/No)	Yes
	Mass (kg)	9.5095
Key customer attributes	Maximum Capacity (kg)	349.3081
	Stair Climbing Feature (Yes/No)	Yes
	Price (BDT)	9500
Final results	Expected market share (%)	0.57
	Sales (BDT)	10,83,00,000
	Profit V (BDT)	6,70,59,000

4. Conclusions and Future Work

In this research, the limitations of traditional approaches to engineering design and problems associated with the multi-criteria design methodologies have been elucidated. In this regard, the DBD methodology is seen as a remedy to these limitations which employs a single-criterion approach to design and select the preferred alternatives consistently and unambiguously. The customer survey was embedded with DCA so that it resembles closely with actual consumer buying behavior. Finally, the complete DBD process has been demonstrated by applying it to a new product design problem.

DBD enables us to reflect customer preferences in the engineering design process of product development. However, difficulties may arise in situations where customers never used the product or customers are little familiarized with the product. This might occur during the development of a completely new type of product whose design has been radically changed. In these cases, customers may find it difficult to respond to the survey due to their lack of product knowledge which eventually may result in unreliable survey data.

In some cases, the design specification may affect the marketing, inventory and distribution costs (Wassenaar et al., 2005). For example, packaging costs may depend on the physical dimensions of the product. The impact of marketing, inventory and distribution cost can be incorporated in the DBD framework in the future. The DBD framework can be made robust by taking account uncertainty into the objective function, constraints and design variables. Thus Decision Based Robust Design can be another possible scope for future efforts to improve the framework.

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