Operationalizing Regulatory Focus in the Digital Age: Evidence from an E-Commerce Context

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Authors: Ji Wu; Liqiang Huang; J. Leon Zhao

Presenter: Shuai Li

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Introduction

Intro for RFT

Regulatory Focus Theory (RFT):

- **Explains how people's regulatory focus influences their methods of achieving goals.**
- For instance:
  - A piece of advertising framed with either promotion-focus or prevention-focus is more persuasive to consumers with the corresponding focus;
  - Positive information, in comparison to negative information,2 is more likely to be relied on by promotion-focused individuals.

Previous Research:

- Traditional Methods: Primarily surveys and experiments to capture people's RF.
- Limitations: Less applicable to business practitioners in digital contexts.

Main idea of this paper

Develop, demonstrate and evaluate Operationalizing Regulatory Focus as an **IT artifact**.

- This paper introduces a novel approach for operationalizing customers’ chronic Regulatory Focus (RF) in the digital age by employing text mining techniques.
  - Leverages advancements in information technology to analyze rich secondary data on customer behavior.
  - Operationalize the long-standing construct of RF, contributing to computational social science.
- **Two main parts of operationalization** in this context:
  - (1) development of a new IT artifact to compute customers’ chronic RF based on the affective dimension of RFT;
  - (2) evaluation of operationalized regulatory focus (ORF) in practice.

Theory Foundations

Regulatory Focus Theory (RFT) **originally** identifies two types of regulatory orientation:

- **Promotion Focus:** Individual's orientation towards achievements, hopes, and aspirations.
- **Prevention Focus:** This orientation is about avoidance, responsibility, and safety.

Additionally, RFT distinguishes between:

- **Situational RF**: This is temporary and can be triggered by specific situations. It is influenced by external factors and can vary depending on the context.
- **Chronic RF**: Considered as a personality trait, chronic RF is stable over a long period. It is an inherent part of an individual's personality and consistently influences their behavior and decision-making.

Research in RFT suggests that the effects of RF manifest in two dimensions: **cognitive** and **affective**.

RFT and Decision Making

How Regulatory Focus (RF) impacts **various stages** of the decision-making process:

- **Information Selection:** Individuals use their RF as a filter for incoming information.

Promotion-focused individuals are inclined to select positive information related to gains; prevention-focused individuals are more attentive to negative information concerning potential losses.

- **Information Processing:** RF also affects how individuals perceive and emphasize different components of information.

Promotion-focused individuals tend to focus on and amplify positive aspects; prevention-focused individuals emphasize negative aspects.

- **Product Choice:** RF significantly influences consumer preferences and product choices. Marketing strategies that align with the RF of the target audience are more effective.

This consistent finding across various studies highlights the significant role of RF in decision making.

RTF and Emotions

Distinct patterns for promotion-focused and prevention-focused individuals.

- **RF and Emotional Responses:** Promotion-focused or prevention-focused individuals experience and express emotions differently in response to positive and negative outcomes.
- **Nature and Magnitude of Emotions:** Brockner and Higgins (2001) suggested that the nature and intensity of an individual's emotional experience are influenced by their RF.
- **Empirical Studies and Measurements:**
  - Crowe and Higgins (1997): used mood questionnaires to measure RF orientation.
  - **Yen et al. (2011) and Arnold et al. (2014):** promotion-focused individuals showing more intense positive emotions in positive outcomes, and prevention-focused individuals experiencing more intense negative emotions in negative outcomes.
  - Liu and Brockner (2015): observed that when an individual's RF aligns with their experienced event, the intensity of their emotions increases.

Research Motivation and Contribution

Motivation

- Past research mainly relied on conventional empirical research methods such as surveys, interviews, and experiments. However, this is difficult to identify customers' RF in the digital age.
- New Opportunities:
  - **E-Commerce Context:** In e-commerce, understanding whether customers are promotion-focused or prevention-focused is crucial for improving personalized recommendation systems and targeted marketing.
  - **Rise of Customer Data:** The interactive nature of e-commerce has generated a vast amount of customer data, providing new avenues for identifying customer RF through secondary data analysis.

To bridge the research gap, the study aims to make a attempt to operationalize RF in the digital era by leveraging the abundant customer data available in online platforms.

Contribution

The development of a method called "regulatory focus discovery" using text mining.

- This method forms the core of Operationalized Regulatory Focus (ORF) and modernizes the use of RFT for the digital age.
- The research enriches design science literature by providing a rigorous analytic model and introducing a novel method, addressing the lack of "invention" work highlighted in existing research.
- The approach is innovative as it applies new technical means to enhance a well-known behavioral theory, making it more relevant and applicable in real-world business contexts.

Research Question

- How can customer RF be operationalized from the affective dimension using text mining on online product reviews?
- How can the operationalized RF (ORF) be validated by a field survey?
- How can the ORF be applied to study the impact of OBC participation on customer purchase behavior conditional on customer RF?

Research Context

- The research context is an e-commerce company that designs, produces, and sells apparel in an Asian market. The company has a proprietary e-commerce platform and a firm-sponsored OBC.
- The paper focuses on the customers who have posted online product reviews and who have participated in the OBC.

Methodology

Operationalization of Regulatory Focus

We explore customer RF via the affective dimension rather than the cognitive dimension

Theoretical Foundation

Regulatory Focus Theory (RFT)

- **RF and Emotional Intensity:** Promotion-focused customers would have relatively weaker negative emotions like disappointment in contrast to prevention-focused customers' stronger negative emotions like anxiety.
- **Sentiment Biases:** Stable over time and consistent across contexts.
- **RF discovery:** Utilizes unique text mining procedures to detect customers' chronic RF
- **Online reviews** could be used to detect customers' trait, providing a consistent form of emotional expression forevaluation across products.

Data Description

- **Data Source:** Data is collected from a e-commerce apparel company, selling in Asian market. The firm also sponsors an online brand community (OBC) to facilitate customer interaction.
- **Collection Time and Details:** Data collected from May 2011 to December 2012, including 3 database: registration database, transaction database, and products database.
- **Extent of Data Collected:** 2,300 customers generated 12,800 reviews on 1,276 products.
- **Data Analysis and Validation:**
    - By using their RF discovery method, they identitified these reviewers' **chronic RF (i.e., the ORF)** in the first round of data analysis.
    - The study used this rich dataset to **validate the application of ORF** in understanding customer purchase behavior. This was done by <u>triangulating data from customers' online reviews, community participation records, and e-commerce transaction records</u>.

Operationalization RF

The study uses **sentiment strength analysis** to extract customer emotional patterns from online product reviews. This method automatically detects the intensity of emotional expressions in the reviews.

Figure 1 plots a flow chart of customers' chronic RF discovery:

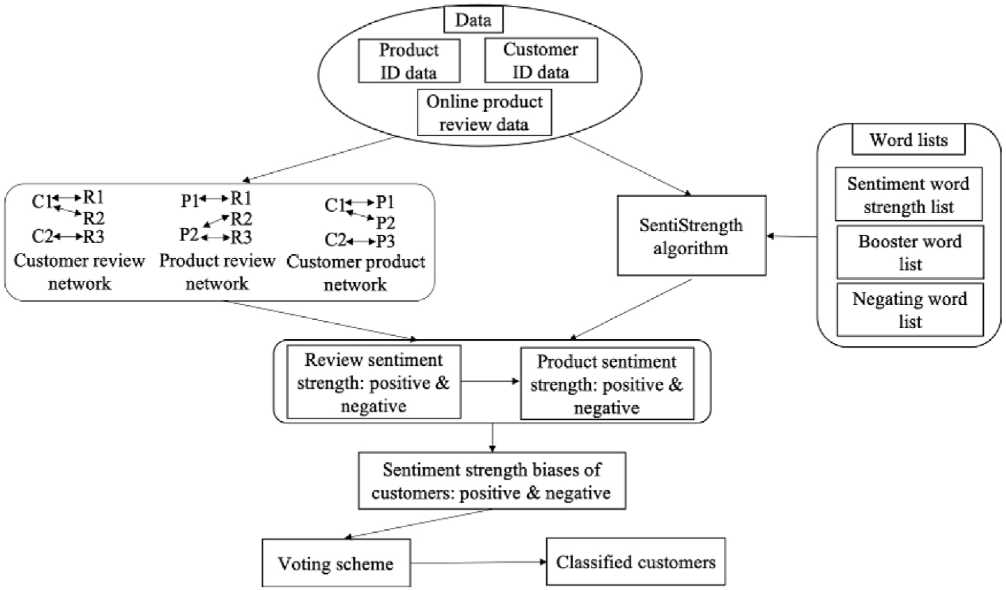

Figure 1. Flow Chart of RF Discovery

Sentiment-Strength Bias:

- Promotion-focused customers tend to express stronger positive sentiment or weaker negative sentiment, indicating a **positive sentiment-strength bias**.
- Prevention-focused customers show weaker positive sentiment or stronger negative sentiment, indicating a **negative sentiment-strength bias**.

Customized SentiStrength Algorithm

- SentiStrength algorithm is a lexical approach to assess emotive sentiment in various contexts, which has been proved to be efficient.
- Customized in Mandarin texts, developing two additional word lists: booster word list (97 words) and negating word list (36 words).

- These adaptations can measure positive and negative sentiment strengths with a scale ranging from -5 to +5.

$$SSP_j^+ = \frac{\sum_{i=1}^{m} SSR_{ij}^+}{m}$$

$$SSP_j^- = \frac{\sum_{i=1}^{m} SSR_{ij}^-}{m}$$

- Then classifying customers as promotion-focused or prevention-focused based on a majority voting scheme by the sentiment-strength biases exhibited in their product reviews: 1 (positive), 0 (neural), -1 (negative)

For each $c_i \in C$ (C is a set of customers)

$SSB_i^+ = 0, SSB_i^- = 0$

For each $r_{ij} \in c_i$(r_{ij} is an online review generated by c_i)

if $SSR_{ij}^+ - SSP_j^+ > 0, SSB_i^+ = SSB_i^+ + 1$

else if $SSR_{ij}^+ - SSP_j^+ = 0, SSB_i^+ = SSB_i^+$

else if $SSR_{ij}^+ - SSP_j^+ < 0, SSB_i^+ = SSB_i^+ - 1$

if $SSR_{ij}^- - SSP_j^- > 0, SSB_i^- = SSB_i^- + 1$

else if $SSR_{ij}^- - SSP_j^- = 0, SSB_i^- = SSB_i^-$

else if $SSR_{ij}^- - SSP_j^- < 0, SSB_i^- = SSB_i^- - 1$

if $SSB_i^+ > 0 \wedge SSB_i^- > 0, c_i$ is classified as promotion-focused

else if $SSB_i^+ < 0 \wedge SSB_i^- < 0, c_i$ is classified as prevention-focused

Figure 2 Voting Scheme for Classification

How chronic RF can be reflected in product evaluation?

- **Left:** Example of a Prevention-Focused Customer (Graph a, ID = 39514)
- **Right:** Example of a Promotion-Focused Customer (Graph b, ID = 44665)

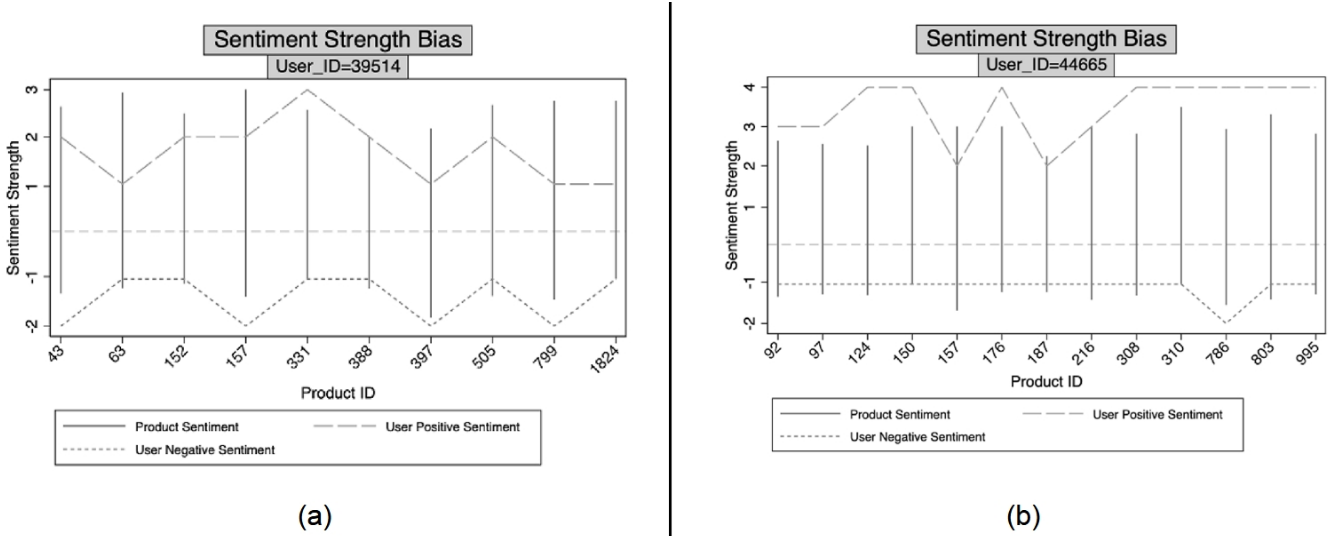

Figure 3. Two Examples

Field Survey Assessment

- The paper also conduct a **field survey** to verify whether their RF discovery method accurately identified individuals' RF.
- Using RF questionnaire based on Haws (2010): 5 promotion-focused and 5 prevention-focused on seven-point Likert scale .
- Statistics: 141 responsesreceived; 124 valid questionnaires; 78.6% female, 53.7% between 25 to 37 years old, over 42.5% have university degree, and 93.2% purchased online frequently
- **Results:**
  - No selection bias. (See Appendix F)
  - Good reliability and correlation of the measurement scores: Both the RF promotion scale and the RF prevention scale were reliable ($\alpha_{promotion}$ = 0.63, $\alpha_{prevention}$ = 0.72 and uncorrelated r = 0.01; Louro et al. 2005).
  - Tight relationship between Survey RF and Sentiment Biases in reviews.(See Appendix G)

- Classification Performance:
  - For the promotion-focused group: Precision was 83.3% and recall was 87.3%.
  - For the prevention-focused group: Precision was 86.2% and recall was 82.0%.
  - The overall classification accuracy of the method was 84.7%.
- Robustness of Classification:

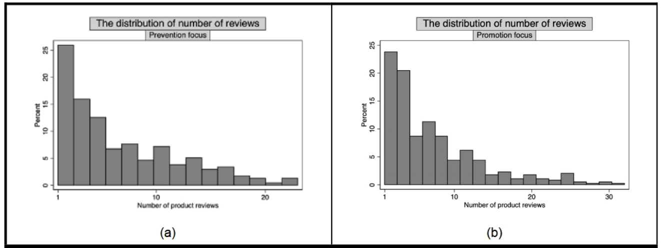

Figure 4. The Distribution of Number of Reviews per Customer

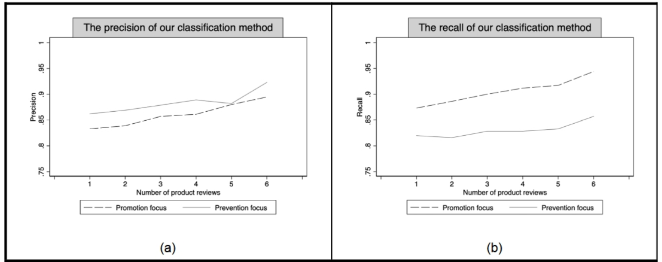

Figure 5. Performance of RF Discovery

Evaluation of ORF

They evaluated ORF by applying it in the domain of consumer purchase behavior in **OBC (Online Brand Communities)**.

- **Previous studies:** OBCs reduce uncertainties about a firm's products and services by providing product information and facilitating communication; Other studies have indicated potential negative consequences of OBC participation.
- The paper proposed that <u>RFT could explain the inconsistent findings</u> regarding the impact of OBC participation on customer behavior.

Hypothesis:

The effect of participation in a customer brand community on purchase behavior is contingent on the customer's RF.

- Specifically, OBC participation has a <u>positive impact on the purchase frequency of promotion-focused customers</u> but a <u>negative impact on the purchase frequency of prevention-focused customers</u>.

Econometrics Model

- Data selection: customers must be members of the brand community and have posted product reviews.
- **Four econometrics issues** needed to be addressed to accurately estimate the causal effects of OBC participation on customer purchase frequency:
  - **Self-selection:** Propensity score matching (PSM, see Appendix H for PSM procedure and results).
  - **Reverse causality:** Predictive tests + Difference in Difference (DiD)
  - **Social network endogeneity:** Including the average purchase frequency of a customer's neighbors ($NeighborPurFreq_{-ij,t}$)
  - **Unobserved customer heterogeneity:** Including user fixed-effects (μ_{ij})

$$\begin{aligned}\log\left(PurFreq_{i,j,i}\right) &= \beta_0 + \beta_1 Treated_{ij} + \beta_2 OBCPart_{ij,t} \\ &+ \beta_3 Treated_{ij} \times OBCPart_{ij,t} + \beta_4 Treated_{ij} \times OBCPart_{ij,t} \\ &\times ReguFocus_{ij} + \beta_5 NeighborPurFreq_{-ij,t} \qquad (3) \\ &+ \beta_6 SalesIntensity_{ij,t} + \beta_7 \log\left(\Pr ice_{ij,t}\right) + \beta_7 TranFee_{ij,t} \\ &+ \mu_{ij} + \theta_t + \varepsilon_{ij,t}\end{aligned}$$

Estimations of models using the DID 1

Table 2. OBC Participation and Customer Purchase Frequency

Variables	Model (1) No Controls	Model (2) Controls	Model (3) Controls, FE, TE	Model (4) Three-Way Difference
Treated	0.025 (0.045)	0.056 (0.045)	0.026 (0.044)	0.024 (0.045)
OBCPart	0.061* (0.035)	0.083** (0.035)	0.022 (0.037)	0.017 (0.037)
Treated × *OBCPart*	0.179*** (0.053)	0.205*** (0.053)	0.191*** (0.053)	0.113* (0.067)
ReguFocus	0.021 (0.027)	0.033 (0.027)		
Treated ×*OBCPart* ×*ReguFocus*				0.170*** (0.055)
NeighborPurFreq		0.173*** (0.030)	0.078** (0.038)	0.079** (0.038)
SaleIntensity		0.379*** (0.038)	0.399*** (0.039)	0.404*** (0.040)
ln(*Price*)		-0.048*** (0.018)	-0.077*** (0.019)	-0.077*** (0.019)
Transfer		-0.004 (0.003)	-0.006* (0.003)	-0.005 (0.003)
Intercept	0.651*** (0.033)	0.227*** (0.105)	-0.135 (0.261)	-0.072 (0.262)
User fixed effects	No	No	Yes	Yes
Time-specific dummies	No	No	Yes	Yes
R^2	0.010	0.055	0.084	0.088

Notes: Standard errors in parentheses; FE = customer fixed specific effects; TE = time-specific effects. **p* < 0.1, ***p* < 0.05, ****p* < 0.01.

Table 2: OBC Participation and Customer Purchase Frequency

Estimations of models using the DID 2

Table 3. Impacts of OBC Participation on Purchase Frequency with Different RF				
Variables	Model (5) Subsample: Prevention Focus		Model (6) Subsample: Promotion Focus	
	Coefficient	SD	Coefficient	SD
Treated	0.215***	0.079	0.132**	0.054
OBCPart	0.093	0.069	0.007	0.044
Treated × *OBCPart*	-0.114	0.098	0.312***	0.063
NeighborPurFreq	0.024	0.078	0.090**	0.044
SaleIntensity	0.465***	0.075	0.377***	0.048
ln(*Price*)	-0.091***	0.035	-0.071***	0.023
TranFee	0.001	0.006	-0.008*	0.004
Intercept	-0.222	0.585	-0.068	0.293
User fixed effects	Yes		Yes	
Time-specific dummies	Yes		Yes	
R^2	0.113		0.095	

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Impacts of OBC Participation on Purchase Frequency with Different RF

Results:

- The inclusion of RF as a variable in the model significantly improves its predictive power.
- The effects of OBC participation on purchase behavior are different for promotion-focused and prevention-focused customers, with a more pronounced impact on the former.

Robustness Check

- To check the validity and reliability of the main results.
- Use different methods such as instrumental variable estimation, inclusion of additional variables, alternative matching algorithm, purchase expenditure and subsample analysis.
- Find that the results are consistent and robust across different specifications and samples, indicating that their findings are not driven by spurious correlations or measurement errors.
- Discuss the limitations and challenges of their robustness tests, such as the difficulty of finding valid instruments, the potential endogeneity of RF, and the trade-off between bias and efficiency.

Instrumental Variable Specification

- **Purpose**: Address endogeneity and self-selection bias.
- **Instrumental Variable**: Review Intensity ($ReviewIntensity_{it}$).
- **Criteria**: Correlated with OBC participation but not with purchase frequency.
- **Result**: Consistent with DID method findings, indicating robustness.

Inclusion of Additional Variables and Alternative Matching Algorithm

- **Additional Variables**:
  - Email validation status ($EmailValidated$).
  - Geographical location ($EasMidWes$).
  - Purpose: Assess relation to OBC participation.
- **New Method**:
  - Logit model with additional variables.
  - Kernel-matching algorithm in PSM.
- **Result**: No significant difference from original DID results.

Purchase Expenditure and Subsample Analysis

- **Focus**: Effect of ORF on relationship between OBC participation and purchase expenditure.
- **Method**: DID analysis for each customer segment.
- **Result**: Supports main findings; ORF influences purchase expenditure impact.

Inclusion of Customer Satisfaction

- **Variable**: DeltaPurchase (change in purchase behavior).
- **Purpose**: Explore impact on purchase frequency.
- **Result**: Positive impact on purchase frequency; main relationships remain consistent.

Ruling Out Reverse Causality

- **Approach**:
  - Descriptive statistics comparison.
  - Probit regression analysis.
  - Unanticipated participation (UPART variable) analysis.
- **Findings**:
  - No significant pre-participation purchase frequency differences.
  - Purchase frequency is a poor predictor of OBC participation.
  - No significant impact of high purchase frequency on OBC participation.
- **Conclusion**: Evidence supports absence of reverse causality between purchase frequency and OBC participation.

Conclusion

Theoretical Contribution

- Developed RF discovery method to operationalize customer regulatory focus via text mining.
- Integrates behavioral science and data science into a design science IT artifact.
- Identified valid instrumental variable for econometric analysis in social media.

Practical Implication

- RF discovery scalable to large numbers of customers.
- More efficient than surveys, without burdening individuals.
- Allows implicit identification of regulatory focus outside awareness.

Limitations and Future Research Directions
Limitations of the Study

- **RF Misclassification**:
  - About 12.5% of individuals misclassified by the RF discovery method.
  - Due to limitations in sentiment analysis and potential field response bias.
- **Data Requirement Limitations**:
  - Method less effective for users with minimal reviews, especially in atypical scenarios.
  - Reliance on sufficient data inputs restricts broader applicability.
- **My Critiques:**
  - Is this a new problem? Why does it matter?
  - What datasets are built/used for the quantitative evaluation? Dataset not sufficient and general.
  - Enough staying power? Theoretical contribution is not enough.
  - How about the methodology?

Future Research Suggestions

- **Controlled Environment Studies**: Explore RF identification accuracy in a lab setting for better results.
- **Cognitive Dimension Exploration**: Extend RF identification beyond emotional evaluations to cognitive aspects.
- **Theoretical Extensions**: Investigate RFT as both an explanatory and predictive model.
- **Marketing Science Integration**: Collaborate with marketing researchers to apply ORF in marketing-oriented questions.

Learning From This Paper

- **How to start a empirical research?**
  - (1) Interesting and contributing questions(Most important)
    - Always don't discuss chanllenge first, but the contribution of your research.
    - Interesting questions rather than sufficient conditions are the reasons for doing this research.
    - However, questions are permited to iterate.
  - (2) Choose one way:
    - i. Way One: Start from a theory
      - We can only get dataset with not sufficient information / not enough variables.
      - We possess a suitable theory and utilize it to model /construct a artifact.
    - ii. Way Two: Start from a data set
      - We have a dataset with sufficient information / enough variables.
      - We can use the dataset to find some interesting phenomenon and then construct a theory to explain it. Furthermore, we can discover phenomena that are counter-intuitive/propose knowledge that exceeds current public coginition.

- **Econometric/ Empirical Analysis:**
  - Finding DID opportunities
  - Rigorous robustness check
  - Changing Perspective:
    - Interesting variable as Dependent Variable
    - Interesting variable as Independent Variable
- **Questions Proposed by Me:**
  - (1) Should a literature review focus on issues or areas?
    - Example: Live-Streaming E-Commerce Product Return
  - (2) How to judge whether dataset is pulishable?
    - Example: Product Return data are interval data.

Thank You !