Developing data-driven QFD: A systematic approach to employing text information using product manuals

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> > 2023년 대한산업공학회 추계학술대회

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Introduction

Background

- QFD as a prominent method for designing new products or services, by measuring the relationships between Customer Requirements (CRs) and Functional Requirements (FRs)
- Many previous works on utilizing QFD for product design (Sireli et al, 2007; Ji et al 2014; Kirgizov, U.A & Kwak, C et al.,2021)
- A data-driven approach to the QFD as a promising research area (Chan, L. et al 2002; Xu et al, 2018; Ha & geum, 2022;)

Motivation

- Limitation of previous works on data-driven QFD
 - Focusing only on CRs when employing data-driven approach (Nahm, 2013; Luo, et al, 2014)

(introducing customers purchase choice rules into the QFD based product planning process to simulate a customer's purchase behavior towards a product)

- Needs to suggest more effective ways on developing data-driven QFD, considering FR constructions and relationship measurements

Objective

- To develop a holistic data-driven QFD framework by employing a systematic approach to the data-driven FR constructions and measurements
- To utilize data mining and text mining techniques to extract proper FRs and quantitatively measure relationship between CRs and FRs

Literature review

In today, big data analytics drive businesses to integrate data analysis into their strategic management.

With the increasing accessibility of data sources, companies are finding it easier than ever to collect customer requirement from online platform.

Previous studies have analyzed mostly customer reviews and identified customer requirements from text.

1. Data-Driven Customer Requirement Analysis

Numerous studies use data-driven techniques to extract customer requirements from text data.

- Chiu et al. (2018) used text mining to predict customer preferences.
- Wang et al. (2019) combined different layers to elicit customer requirements.
- Xu & Dang. (2020) likewise developed an automated cause-and-effect diagram using a data-driven approach

Literature review

- 2. Quality Function Deployment (QFD) as Data-Driven
- Recent advancements include the integration of data analysis with QFD.
- Jin et al. (2014) prioritized engineering characteristics based on customer reviews.
- Jin et al. (2015) used text mining for technology-driven QFD.
- Özdağoğlu et al. (2018) made an effort to integrate QFD and topic modeling.
- Huang et al. (2022) proposed an approach that combines LDA and Interval Grey Number QFD.
- Asadabadi et al. (2022) designed a method for automating the QFD process using text mining.

However, these studies mostly focused on customer requirements (CRs) and overlooked functional requirements (FRs). Given that QFD considers both CRs and FRs, a holistic framework addressing both is suggested.

Overall Framework

topic modeling

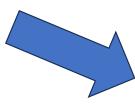


Product

Manual

Extracting CRs Collecting data & Tokenizing, Preprocessing remove stop word Extracting CRs using

Variable (Importance; weight) creation based on frequency





Co-occurrence

Topic extraction Keyword approach

> Developing a matrix

sentiment score

Managing CR-FR Interactions

1) Evaluating CRs and FRs are related through high co-occurrence

- 2) No corresponding FRs to a specific CR
- 3) No corresponding CRs to a specific FR

Extracting FRs Collecting data & Tokenizing, Preprocessing remove stop word Table of Contents Distinguishing **Images** information type Plain Text Flowchart Extracting FRs Venn-Diagram

Variable (Importance; weight) creation based on frequency

Framework for CRs

Collecting data

Collecting review data from online

Preprocessing

Using collected data

- **Data Cleaning**: Removing unnecessary data, handling duplicates, and fixing format errors.
- Outlier Treatment: Managing unusual data.
- **Data Transformation**: Modifying data formats.
- Scaling and Normalization: Adjusting data scales.

Extracting CRs

- 1.1 Topic modeling
- Topic Selection
- 1.2 Keyword-based approach
- Select keyword with high frequency
- 2. Generating variable
- Importance : the more frequent, the more importance
- Sentiment- score : representation of text - keyword (positive, negative, neutral)



Framework for FRs

Collecting data

Collecting manual from company website

Preprocessing

• Same CRs process

Distinguishing information type

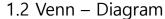
- TOC: manual structure
- Image : Product specifications
- Plain Text : product details

Extracting - FRs

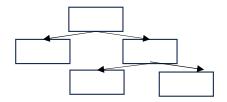
- 1.1 Flowchart
- First, select TOC page
- Second, select specification images
- Third, select detailed product

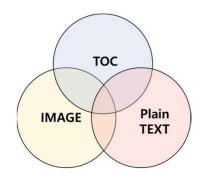
description (mostly text)

- Finally, remove unnecessary page.
- repeat Preprocessing



- keywords occurs in each Information type
- 2. Generating variable
- Importance : the more frequent, the more importance
- Sentiment- score : representation of text - keyword (positive, negative, neutral)





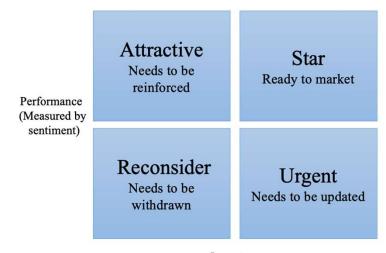
Framework for Evaluating

Evaluating CR-FR relationships

- 1. Co-occurrence matrix
- checking for missing rows or columns in each matrix
- → support to product design
- co-occurrence matrices facilitate straightforward keyword comprehension and intensity.
- Visualization augments lucidity and insights.
- 2. IPA matrix
- capture sentiment alignment with CRs
- assist in decision-making by identifying which features to focus on

	assembled	guide	estimate	assurance	bougth
assembled	20.0	0.0	0.0	0.0	0.0
guide	0.0	8.0	0.0	0.0	0.0
estimate	0.0	0.0	2.0	0.0	0.0
assurance	0.0	0.0	0.0	6.0	0.0
bougth	0.0	0.0	0.0	0.0	2.0

Co-occurrence



IPA framework

Importance (Measured by frequency)

Case illustration

1. Data collection

CR : online platform (amazon.com)

• FR : company website

(bosch – washing machine)

CDa	FRs			
CRs	TOC	Text	Image	
period	detergent	detergent	panel	
time	laundry	button	detergent	
clothes	settings	laundry	setting	
quality	panel	remove	clothes	
delivery	safety	setting	control	
money	blocked	hose	door	
noise	removing	depending	display	
value	drawer	press		
vibration	display	change		

Table 1

2. Data Preprocessing (both)

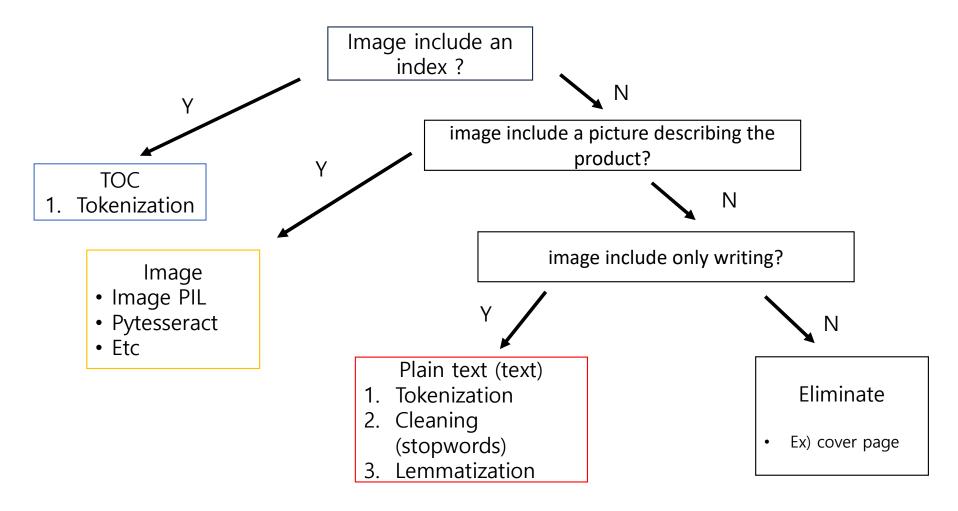
- Data Cleaning: Removing unnecessary data, handling duplicates, and fixing error
- Outlier Treatment: Managing unusual data.
- Data Transformation: Modifying data formats.
- Feature Engineering: Creating new insights.
- Scaling and Normalization

Table 1 lists extracted keywords for CRs and FRs

(their high frequency occurrence)

→ conduct <u>steps 1,2 for CRs</u> and <u>steps1,2,3(distinguish) for FRs</u>

Case illustration (FR – 3. distinguish)



Case illustration (4. generating variable)

- To assign weights, the frequencies of CRs and FRs are normalized to values between 0 and 1, and these values are utilized as weights.
- At this point, no threshold is applied to the frequencies of weighted CR and PF; in other words, weights are assigned to all keywords without imposing a frequency limit, such as freq > 2.
- The sentiment scores assigned to CRs and FRs are based on a threshold of 0.1.

CRs	Importance	sentiment_score	
period	1	0	
time	0.676271	0	
clothes	0.383051	0	
quality	0.359322	0	
delivery	0.347458	0	

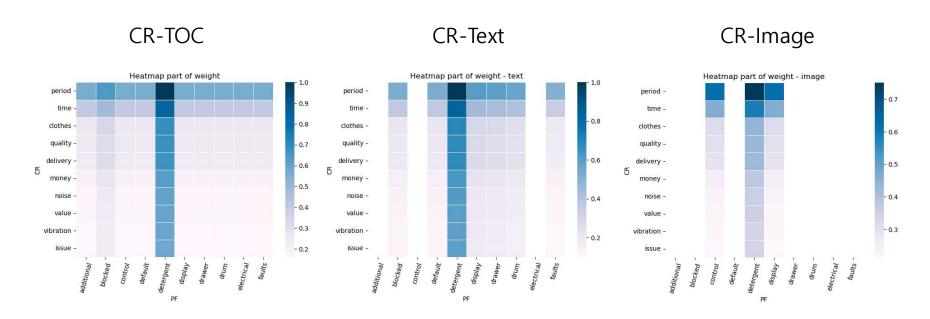
FRs(TOC)	Importance	sentiment_score
detergent	1	0
laundry	0.71428571	0
settings	0.42857143	0
panel	0.42857143	0
safety	0.42857143	0.4215

Positive

Case illustration (4. generating variable - Importance)

Importance

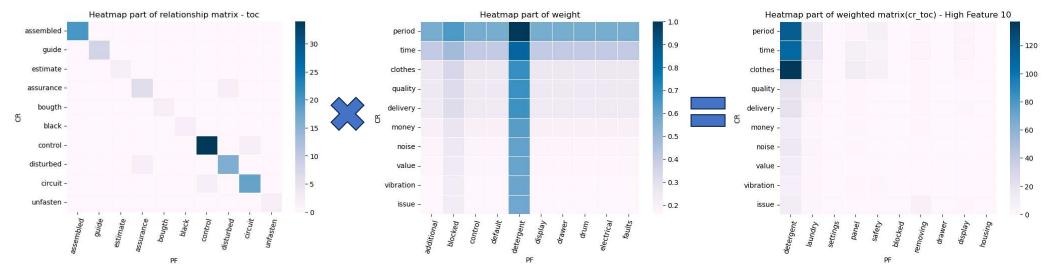
- Before construct the relationship matrix, we derived the weights (importance) for CRs and FRs
- Importance is a standardized variable generated based on frequency.
- The visualizations provided depict a subset of the importance values for the following relationships, presented in sequence: CR-TOC, CR-Text, and CR-Image.



1) Co-occurrence matrix

- Defined Relationship Matrix (CR-TOC, CR-text, CR-Image)
- checking for missing rows or columns in each matrix
- · support to product design

CR-TOC



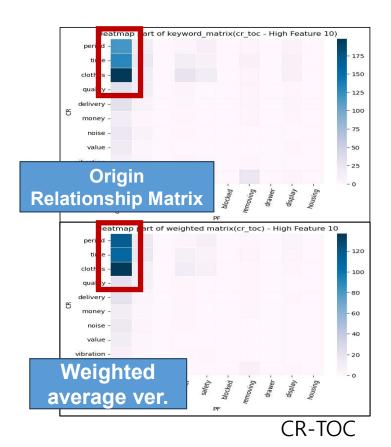
Relationship matrix

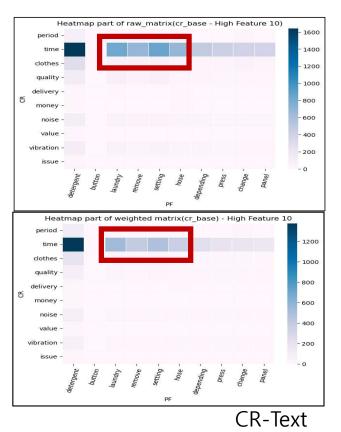
Importance matrix

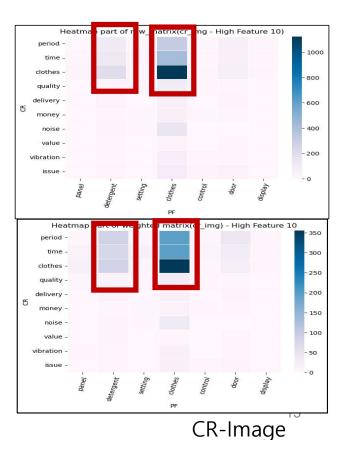
multiplied by the Relationship matrix to apply the importance

1) Co-occurrence matrix

• The weighted average version of the Relationship Matrix enhances the relevance of CRs and FRs.

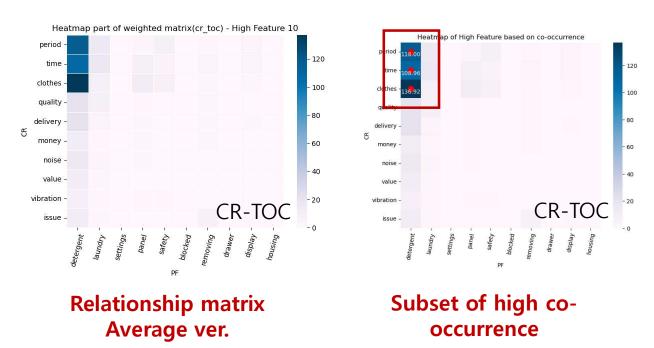






1) Co-occurrence matrix

- Additionally, detecting the substantial co-occurrence of CRs and FRs. (High value)
- The Relationship Matrix offers a more comprehensive analysis than a simple examination of keyword occurrences.
- Its applicability to the entire plot, rather than just subplots, contributes to a better comprehension of data distribution.



Subset of high co-occurrence

Heatmap of High Feature based on co-occurrence

period 1999
sound tharge there is no center shirt buck circuit tube didnt build 1) There are no corresponding FRs

House thousand 2) There are no corresponding CRs

thousand 2) There are no corresponding CRs

for a specific CR.

thousand 2) There are no corresponding CRs

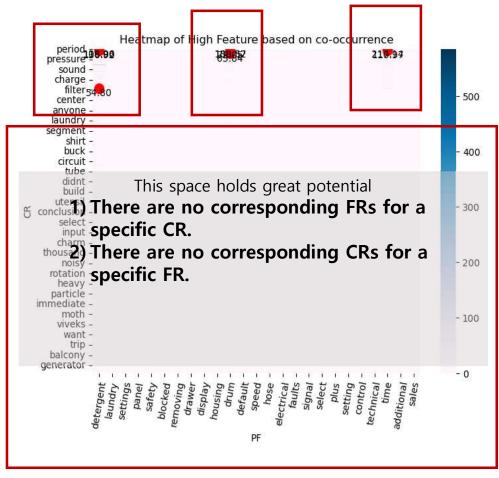
for a specific FR.

-100

Friday 1998

CR-TOC

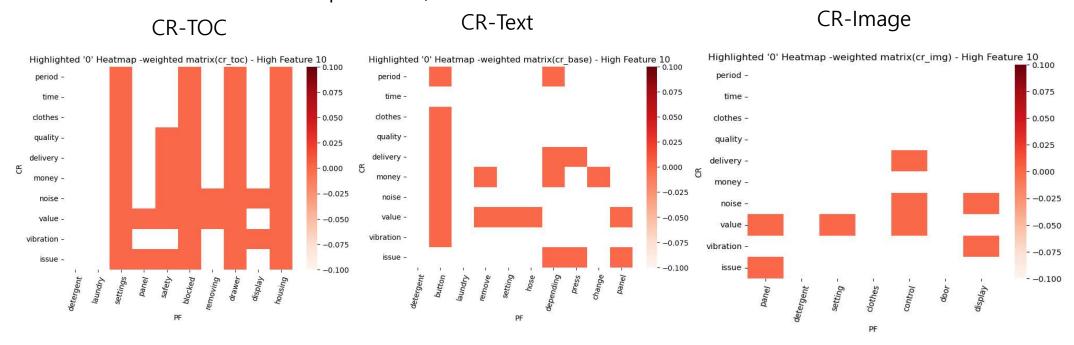
1) Co-occurrence matrix



- 1. In the figure, CRs (word: period, filter,..) exhibit a high co-occurrence of many points
- 2. Period-detergent, Period-drum, etc. can be considered as important.
- → Components and consumables that are periodically used, such as, 'detergent','drum'
- → Customers are concerned about consumables
- 3. The boxes correspond to the risks associated with 2) and 3).
- -> Thorough examination of these boxes is warranted

2) No corresponding FRs to a specific CR

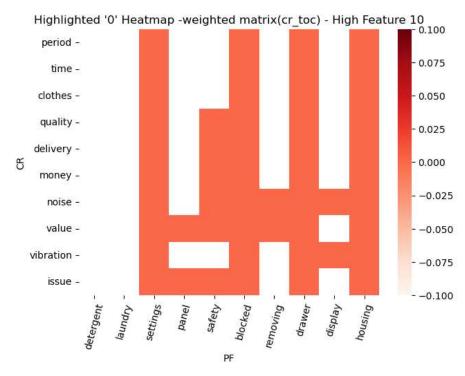
• All matrices do not correspond to 2).



• In this case, there is unlikely to be a critical risk

3) No corresponding CRs to a specific FR

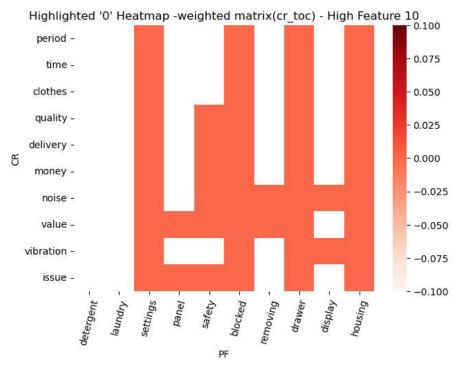
CR-TOC matrices correspond to 3)



- In the CR-TOC Relationship Matrix, FR: 'setting', 'blocked',' drawer' etc. have no corresponding FRs
- -> Although it is a risk, there is no need to delete it. However, it is essential to consider whether it is truly necessary.

3) No corresponding CRs to a specific FR

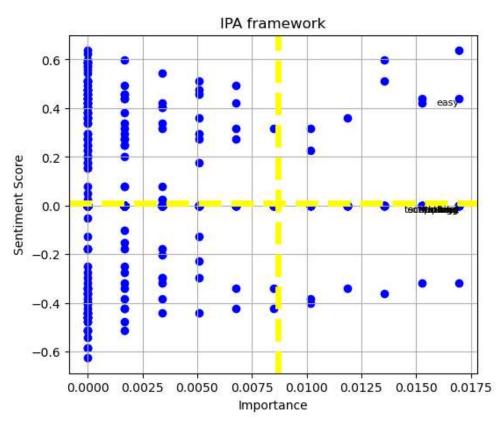
CR-TOC matrices correspond to 3)



- In the CR-TOC Relationship Matrix, FR: 'setting', 'blocked',' drawer' etc. have no corresponding FRs
- -> Although it is a risk, there is no need to delete it. However, it is essential to consider whether it is truly necessary.

Case illustration (5. Evaluating – IPA Matrix)

creater than or equal to the lower 90% of the data and less than or equal to the upper 10% of the data



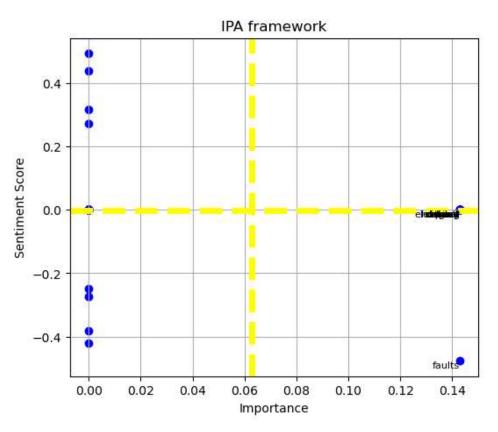
word	Importance	sentiment	score
something	0.016949	neutral	0.0000
show	0.016949	neutral	0.0000
prompt	0.016949	neutral	0.0000
duration	0.016949	neutral	0.0000
laundry	0.016949	neutral	0.0000
technology	0.016949	neutral	0.0000
panel	0.016949	neutral	0.0000
easy	0.016949	positive	0.4404
steel	0.016949	neutral	0.0000
change	0.016949	neutral	0.0000

'Easy' is Star FRs.

- performance and importance are at high levels, indicating well-defined FRs and positive customer perception

Case illustration (5. Evaluating –IPA Matrix)

TOC



word	Importance	sentiment	score
drawer	0.142857	neutral	0.0000
display	0.142857	neutral	0.0000
housing	0.142857	neutral	0.0000
drum	0.142857	neutral	0.0000
default	0.142857	neutral	0.0000
speed	0.142857	neutral	0.0000
hose	0.142857	neutral	0.0000
electrical	0.142857	neutral	0.0000
faults	0.142857	negative	-0.4767
signal	0.142857	neutral	0.0000

'Faults' is Urgent

- high importance but low levels of performance, as measured by customer feedback

Conclusion

Contribution

- The primary contribution of this study is the introduction and application of data-driven QFD.
- This approach is expected to enhance product design and quality management processes, aligning them more
 effectively with customer requirements.
- Additionally, it highlights the practicality of data integration throughout the entire QFD process.

Limitation

- Complexity of Analysis: The study suggests advanced methods for data-driven PF extraction, but lacks in-depth explanation for methodology
- Data Integration Hurdles: Integrating data from various sources is not thoroughly addressed, potentially limiting practical application.

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