DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

Jurnal Rekayasa Sistem Industri
Volume 13 No 1 - April 2024
http://journal.unpar.ac.id/index.php/jrsi/index
ISSN 2339-1499 (*online*) – ISSN 0216-1036 (*print*)

Disampaikan : 6 Juni 2023
Direview : 13 Juni 2023
Diterima : 7 Juli 2023

Revolution in New Product Development: Unleashing the Power of Natural Language Processing to the Whole Product Development Process – A Literature Review

Gerald Shan Benediktus Simanullang[1], The Jin Ai[2]
[1,2] Departemen Teknik Industri, Universitas Atma Jaya Yogyakarta
Jalan Babarsari 44 Yogyakarta
Email: 195603173@students.uajy.ac.id, the.jinai@uajy.ac.id

Abstract

Customer satisfaction is a key success factor for a business. To provide products that meet customer satisfaction, companies must be able to understand the customers' needs and desires. Technological developments nowadays have helped companies to understand customer desires more easily so that companies can provide products that satisfy their customer. Natural Language Processing (NLP) is a technology that allows computers to process human language. NLP is also commonly referred as text-mining. NLP has been utilized in the New Product Development (NPD) process. We compiled studies related to NLP and NPD and conducted a literature review to map out how far NLP has been utilized in NPD processes. We found that in this era of Big Data, current NLP studies most often have the goal to process text data from online reviews on e-commerce and from social media. By using NLP, large amounts of data can produce valuable Voice of Customer (VOC) information for product development. We also found that NLP technology also has been utilized in other NPD processes that do not involve VOC, such as the design stage, document processing, and extraction of requirements in the NPD process.

Keywords: natural language processing, new product development, voice of customer, Big Data

Abstrak

Kepuasan pelanggan merupakan faktor kunci kesuksesan sebuah bisnis. Agar dapat menyediakan produk yang memenuhi kepuasan pelanggan, perusahaan harus dapat memahami kebutuhan dan keinginan dari pelanggannya. Perkembangan teknologi pada saat ini telah membantu perusahaan agar dapat memahami keinginan pelanggan dengan lebih mudah sehingga perusahaan dapat menyediakan produk yang memenuhi kepuasan pelanggan. *Natural Language Processing* (NLP) merupakan teknologi yang memungkinkan komputer mengolah bahasa manusia. NLP telah dimanfaatkan para pelaku bisnis dalam proses *New Product Development* (NPD). NLP juga sering disebut dengan istilah *text-mining*. Kami mengumpulkan penelitian-penelitian terkait dengan NLP dan NPD dan melakukan tinjauan literatur untuk memetakan sampai sejauh mana NLP telah dimanfaatkan dalam proses NPD saat ini. Kami menemukan bahwa dalam era *Big Data* saat ini penelitian-penelitian NLP paling sering memiliki tujuan untuk mengolah data teks dari ulasan online pada e-commerce dan dari media sosial. Dengan menggunakan NLP, data dalam jumlah besar dapat menghasilkan informasi berupa *Voice of Customer (*VOC) yang berharga untuk pengembangan produk sebuah bisnis. Kami juga menemukan bahwa teknologi NLP juga telah dimanfaatkan dalam proses NPD lain yang tidak melibatkan VOC, seperti tahap desain, pengolahan dokumen hingga ekstraksi kebutuhan-kebutuhan dalam proses NPD.

Kata kunci: *natural language processing, new product development, voice of customer, Big Data*

Introduction

Providing products, goods or services, that meet customer expectations is crucial for every business to compete in the market. Companies compete with each other to satisfy customers by offering quality products at prices that customers can afford, according to their target market. In a short period of time, various new products continue to emerge even before the needs of customers change (Gürbüz, 2018). These new products can be innovative new products or improvements of the existing products (Chunawalla, 2008). There are stages that a company goes through before finally launching a new product. Generally, the process of developing a new product starts with the discovery of an idea. The idea then goes through an evaluation process to determine the company's ability to create the product and whether the sale of the product will be profitable for the company. Next is the product design and prototype creation process. The final stage is product launch and postlaunch evaluation.

In order to provide products that meet customer needs, businesses must understand their customers' expectations. The opinions of customers about a product are known as the Voice of Customer (VOC). Conventionally, companies collect VOC through questionnaire surveys or direct interviews with customers. However, surveys and interviews can be complex processes, require significant costs, and be subjective in nature (Tezuka & Tanaka, 2005).

With the advancement of technology, conventional methods for collecting VOC are slowly being left behind. In the current era of Big Data, companies no longer need to visit customers to gather their opinions. Customers today can easily provide reviews about the products they purchase through the review features available on various e-commerce websites. Customers also often upload posts reviewing the products they have recently used on their social media platforms. Furthermore, social media posts by users about their daily thoughts also provide valuable data that can serve as valuable information for businesses (Choi et al., 2020).

Reading hundreds to thousands of customer reviews one by one requires a significant amount of time and effort. Keeping up with every social media user's posts is impossible to accomplish. Therefore, the next challenge that arises is how to transform the vast amount of VOC data into meaningful insights for decision-making within the company. To address this problem, the assistance of computational technology is required.

Natural Language Processing (NLP) is a field of Artificial Intelligence that enables computers to understand human language in written or spoken form. This technology has been widely adopted by companies in their processes for developing new products. The most popular use of NLP today is in processing large volumes of customer reviews to extract valuable information about customer responses to a product. However, in our research, we have found that NLP also plays a role in the development of new products that do not involve the VOC, such as in the design process, organizing documents, and more.

To the best of our knowledge, there is no existing research that specifically addresses the use of NLP throughout the entire NPD process. We found there are literature reviews that summarize reseraches of VOC analysis using NLP. However, since the NPD process extends beyond VOC analysis, we conducted an exploration to investigate whether NLP technology can be applied in other stages of the NPD process.

By gathering concurrent research studies related to NLP and NPD, the research questions in this study are as follows: 1) In which specific stages of the NPD process has NLP been utilized? 2) What is the role of NLP in the NPD process? 3) How can NLP be further developed in the future for product development processes?

Methodology

Ramdhani et al. (2014) outlined the initial step in conducting a literature study is choosing a review topic. This stage involves determining search keywords based on the topic under investigation. In this research, we established two search keywords: "natural language processing product development" and "natural language processing product improvement." These keywords were chosen to obtain studies that explicitly involve NLP and NPD.

The next step after choosing a review topic is searching and selecting appropriate articles (Ramdhani dkk, 2014). This is a stage for gathering articles and selecting them based on relevance. A literature review research typically includes a selection of articles such as theoretical papers, review articles, and empirical research studies. The first keyword yielded a total of 78 articles, while the second keyword resulted in 6 articles. Thus, the total number of articles obtained is 86. The search was conducted using Scopus, a multidisciplinary research database provided by Elsevier.

The next step is to eliminate irrelevant articles in this study. The relevant articles for this study are those that explicitly utilize NLP in one or more stages of the NPD process. The elimination process involves assessing the objectives, methodologies, and research findings through the abstracts of each article. For example, there may was a study that aimed at NPD through VOC analysis using Correspondence Analysis (CA). Since CA is not part of NLP, this study is considered irrelevant for this research. Consequently, out of the total 86 search results, 44 articles are considered relevant. There is no set minimum number of articles established for conducting a literature review. The number of articles required varies depending on the research objectives, disciplinary field, and scope of the topic under review. According to Lovaglia (1991), the question of the "ideal number of references" is answered by considering adequacy. Different writers may have their own views on what constitutes a sufficient number of references for an article.

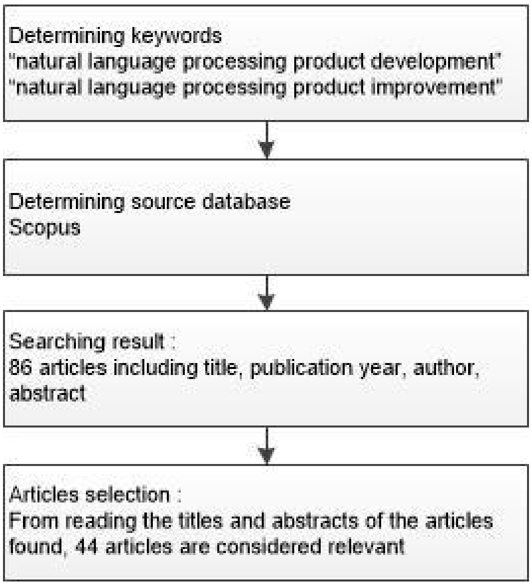

Figure 1. The process of searching and filtering articles.

Ramdhani et al. (2014) proceeded to the final step before writing the literature review, which is analysing and synthesizing the literature. the articles to be included in the literature review have been gathered, the next step involves analyzing each article by breaking it down and identifying the key information it presents. Next, the articles are synthesized, bringing together their findings and allowing for the identification of conclusions that can be drawn from the literature.

Literature Review Findings

In the literature review findings of the discovered studies, we generally classify the researches into two groups: VOC-related and non-VOC-related. VOC-related refers to studies that involve customer reviews or social media posts from internet users, while non-VOC-related encompasses studies that involve electronic documents used in the product development process.

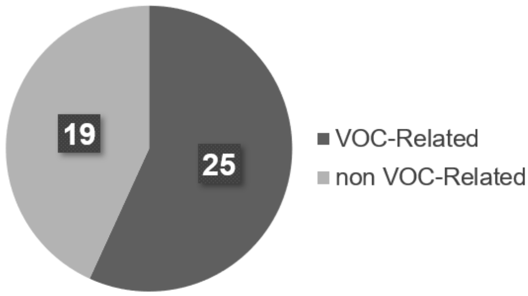

Figure 2. Comparison of the number of VOC-Related vs non-VOC-Related studies.

A total of 25 studies were found that focused on customer opinions. The main objective of these studies was to understand feedback from consumers on a large scale. Table 1 provides an overview of the studies related to customer opinions (VOC-Related).

Furthermore, 19 studies were found with topics unrelated to customer opinions. These studies had various objectives, such as assisting the design process, organizing Engineering Change Request (ECR) documents, identifying required requirements, and so on. An overview of the related studies is presented in Table 2.

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

Discussion

NPD theories overview

The process of developing a new product is a lengthy one that involves a series of evaluations and decision-making. Generally, the development of a new product begins with ideation, idea screening, concept development, and concept testing. These processes are stages before the physical development of the product development, where companies determines the best ways to produce the product, materials to be used, product design, and evaluation of the product's market potential. (Trott, 2017).

The next stage involves product design and the production of several prototypes of the product. These products are then launched for market testing to observe the reactions of potential customers. Once the necessary procedures and evaluations have been completed, the new product will proceed to large scale production.. Tzokas et al. (2014) present a visual representation of the explained NPD process, as shown in Figure 3.

VOC-related Studies

In a competitive business world, a deep understanding of customer needs and the development of appropriate products can be the key to success. Researchers have been created various approaches in order to gain valuable insights from customer reviews to understand customer needs.

Ramaswamy and DeClerck (2018) conducted a study to explore various uses of Deep Learning and NLP. The combination of these two techniques enables the creation of models and algorithms for understanding and processing human language. Deep Learning techniques like convolutional neural networks and recursive neural networks can identify important text features, including understanding sentences, processing words, and recognizing entities. These methods are utilized in tasks such as categorizing text, analyzing sentiment, translating languages, and understanding natural language. By leveraging the power of Deep Learning and NLP, researchers can develop intelligent systems that can understand and interact with everyday-used human language. These systems are particularly valuable for automatically and efficiently interpreting complex customer reviews.

Since 2013, research has been conducted to analyze unstructured text from customer feedback using NLP. For example, Guo et al. (2013) proposed a solution to transform unstructured needs by combining natural language processing techniques and psychological projection. Their approach involves clustering unstructured needs based on natural language semantic similarity and mapping those needs to technical product features using the Gestalt logic system. In the same year, Ittoo & Bouma (2013) created a system called ExtTerm, a specialized term extraction system designed for extracting terms from rarely used, non-standard texts that contain domain-specific content, such as customer complaint emails and engineers' repair notes. Chen et al. (2013) also proposed an ontology-learning customer needs representation (OCNR) system, which contributes to addressing the problem of obtaining accurate statements of needs for initial product development processes. This system utilizes NLP to process customer statements, overcoming the limitations of conventional methods that rely on inaccurate information.

The use of NLP techniques for understanding customers' reviews continue to develop. In 2017, Akella et al. introduced an approach to accurately classify and assign concern codes into customer verbatims. Then, in the same year, Aguwa et al. introduced a novel approach to analyze and interpret ambiguities in the VOC using association rule learning, transforms qualitative text into standardized quantitative format, and creates the Integrated Customer Satisfaction Index (ICSI), which maps customer feedback and determine customers' satisfaction levels. Furthermore, in 2019, Timoshenko and Hauser proposed an approach using convolutional neural networks to eliminate non-informative content reviews to make analysis process more efficient.

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

Table 1. Outline of VOC-related studies

	Author(s)	Outline
1	Gozuacik et al. (2021)	Proposing a comprehensive social media-based opinion retrieval system utilizing machine learning and NLP techniques, with Google Glass as a relevant use-case.
2	Han & Moghaddam (2021)	Creating a rule-based methodology to extract and analyze sentiment expressions from user reviews, effectively mapping individual users' sentiment expressions to relevant attributes.
3	Mokadam & Suresh (2020)	Proposing the study of Aspect Detection in qualitative analysis of customer reviews, using eco-friendly products as an illustrative example.
4	Zhou et al. (2020)	Proposing a Neural Personal Discrimination (NPD) approach to extract personal attributes from posts, connect related posts with similar attributes, and learn collective emotions using adversarial discriminators and attention mechanisms.
5	Cataltas et al. (2020)	Proposing a text analysis method to detect defective features in products by identifying negative opinion tendencies within clustered customer reviews.
6	Rohman et al. (2020)	Applying NLP techniques as a pre-processing step in sentiment analysis of product reviews in marketplace settings, utilizing Naive Bayes and K-NN algorithms to analyze the expressed sentiment in reviews.
7	Sun et al. (2020)	Introducing a dynamic method for mining user requirements to enhance product design by analyze evolving product attributes and identifying changing user preferences over time for continuous improvement.
8	Hou et al. (2019)	Proposing a method to identify and organize customer preferences in online reviews, extending beyond traditional focus on product features, to inform product development and capture a broader range of likes and dislikes of reviewers.
9	Liu et al. (2019)	Demonstrating the significance of psychographic segmentation in predicting users' online purchasing preferences across diverse product categories.
10	Dalpiaz & Parente (2019)	Introducing RE-SWOT, a tool that uses competitor analysis and NLP algorithms to gather requirements from app store reviews, evaluated for effectiveness with product managers to enhance the requirements elicitation process..
11	Timoshenko & Hauser (2019)	Proposing a machine-learning approach that utilizes a convolutional neural network and dense sentence embeddings to optimize content selection and improve the efficiency of qualitative analysis by filtering out non-informative and repetitive content.
12	Hou et al. (2019)	Proposing an approach to capture changes in user expectations and evaluate product improvement strategies by analyzing online reviews of two generations of products, demonstrated through a case study on Kindle e-readers.
13	Lai et al. (2019)	Analyzing dynamic internet data to gain insights into product-design requirements based on users' stochastic product choice behaviors, including features, performance levels, and quantity requirements.
14	Ramaswamy & DeClerck (2018)	Exploring various Deep Learning and Natural Language Processing (NLP) technologies to enhance the analysis of contextual information for capturing customer feedback more effectively.
15	Lin (2018)	Developing a text mining approach specifically designed to capture user experience, with the goal of aiding product designers and developers in understanding user purchase behavior and identifying critical product features.
16	Rathore & Ilavarasan (2017)	Proposing a novel approach to analyze users' reactions to a new product launch using Twitter data, gaining valuable insights into users' sentiments and opinions before and after the launch.
17	Aguwa et al. (2017)	Developing an innovative approach that uses association rule learning and text mining techniques to analyze customer feedback and create an Integrated Customer Satisfaction Index (ICSI) for mapping satisfaction levels.
18	Akella et al. (2017)	Introducing an approach to accurately map customer verbatim to concern codes by leveraging advanced natural language text classification techniques on verbatim inputs from various transactional systems and social media content.
19	Nikumanesh & Fathi (2017)	Proposing an innovative algorithm to mine online product reviews for improved decision-making in purchasing and product enhancement, involving feature extraction from OCRs and attribute categorization based on expert perspectives.
20	Ullah et al. (2016)	Proposing an NLP-based analysis of emotional content in a large dataset of online product reviews.
21	Li et al. (2015)	Applying Emerging Pattern Mining, this paper addresses challenges faced by hotel managers in responding to evolving traveler concerns by identifying emerging hotel features of interest to international travelers.

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

Table 1. Outline of VOC-related studies (continued)

	Author(s)	Outline
22	Shamim et al. (2014)	Describing an opinion mining system that empowers consumers and enterprises by utilizing innovative review and feature ranking methods to identify critical product features from a large volume of consumer reviews.
23	Chen et al. (2013)	Proposing an ontology-learning customer needs representation (OCNR) system that utilizes NLP tools to accurately acquire need statements for the front-end process of product development, overcoming limitations of conventional methods.
24	Ittoo & Bouma (2013)	Introducing ExtTerm, a novel system for extracting relevant terms from sparse, ungrammatical domain-specific texts like customer complaint emails and engineers' repair notes, addressing the challenges of term extraction.
25	Guo et al. (2013)	Proposing a solution to transform unstructured requirements by combining NLP and psychological projection techniques, enabling effective mining and analysis.

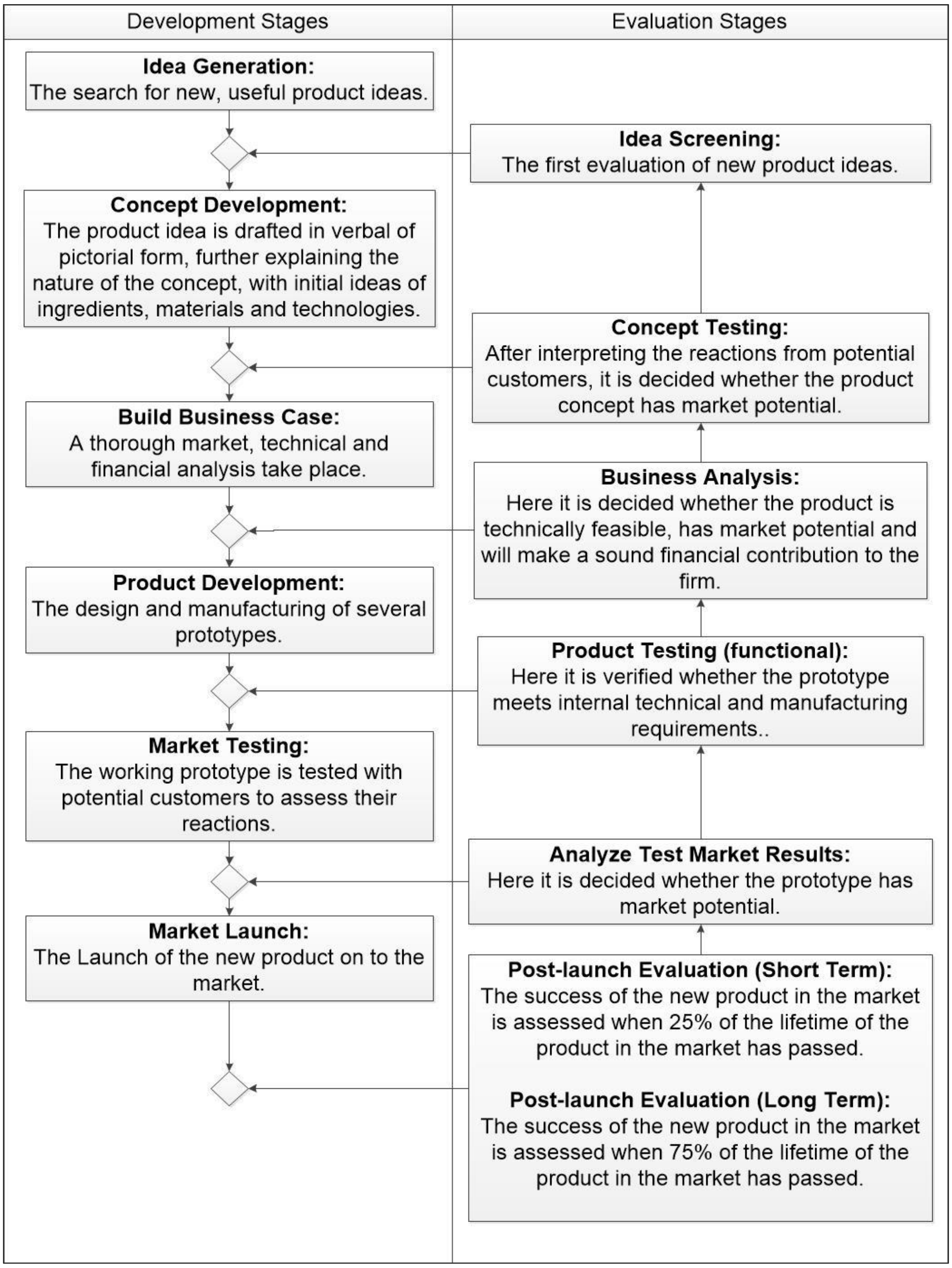

Figure 3. The general process flow of new product development. (Tzokas et al., 2014)

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

Table 2. Outline of non VOC-related studies

	Author(s)	Outline
1	Arnarsson et al. (2021)	Presenting a method using NLP and document clustering to identify related Engineering Change Request (ECR) documents efficiently, reducing search time and organizing results with labeled clusters.
2	Wang et al. (2021)	Proposing a holistic method for developing complex products that leverages a neural network-assisted technological evolution process to mitigate the negative effects of complexity.
3	Schweitzer et al. (2021)	Introducing a framework that aligns requirements for AI with the System Model in Virtual Product Development (VPD), ensuring accurate and high-quality data for AI applications.
4	Pan dan Stark (2020)	Introducing an approach to identify Engineering Change (EC) affected components using component and predicted properties with a hierarchical structure and distinct label communities.
5	Riesener et al. (2020)	Developing a data-driven approach for processing engineering change requests through a literature-derived description model using text mining and natural language processing techniques
6	Horber et al. (2020)	Proposing an approach that links requirement and evaluation criteria models through classification and rule-based derivation, ensuring consistent evaluation criteria.
7	Arnarsson et al. (2019)	Comparing Search Engine and NLP algorithms to expedite retrieval of related engineering documents, transforming manual searching into seconds by efficient searching and ranking based on relevance and significance.
8	Zichler dan Helke (2019)	Automating the conversion of OEM's unstructured Customer Requirement Specifications (CRS) into structured language compatible with suppliers using NLP tools for streamlined and accurate communication.
9	Qie et al. (2018)	Proposing an AI framework that automates requirement analysis and model creation using deep learning and NLP, enhancing product development efficiency and quality.
10	Kim et al. (2018)	Proposing a method to extract and analyze technological data from patents, enabling a deeper understanding of trends and impacts by leveraging patent information.
11	Abad et al. (2017)	Analyzing interruptions in Service-Oriented Software Development (SOSD) projects and their impact on task duration using text classification, NLP, and time series analysis, aiming to improve project performance.
12	Madhusudanan et al. (2017)	Proposing a method for extracting and analyzing expert knowledge from text documents related to aircraft assembly problems, using a pipeline of natural language processing tools.
13	Kleiza et al. (2016)	Proposing an integrated semantic search tool concept that simplifies the search process by combining natural language processing, search engines, and desktop integration frameworks.
14	Guo et al. (2014)	Introducing a new evaluation model, the proportional 2-tuple fuzzy linguistic screening evaluation model, along with a preference-preserving transformation technique based on canonical characteristic values.
15	Christophe et al. (2014)	Proposing a methodology that combines multiple sources and computer-based methods to elicit and refine needs, demonstrated through a case study.
16	Wen et al. (2013)	Introducing CLT-ROM, a method to facilitate online collaboration in cross-language environments for international product development.
17	Dabbish et al (2011)	Introducing a method for extracting component associations in engineering projects by mining design discussion transcripts and constructing networks based on relational text analysis.
18	Lv et al. (2005)	Creating a knowledge management system that enhances knowledge reuse in product development by incorporating Chinese natural language processing techniques for efficient knowledge reasoning and utilization.
19	Prabhu et al. (2001)	Presenting a system that automatically extracts part information from engineering drawings, utilizing heuristic search and natural language processing techniques for efficient dimension interpretation and callout analysis.

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

One of the popular NLP approaches that often to be used is ‘sentiment analysis’. Sentiment analysis is the process of identifying writer’s sentiment in text they wrote, such as product reviews or social media posts. The purpose is to determine whether the sentiment is positive, negative, or neutral. For example, a study by Rathore & Ilavarasan (2017) analyzed Twitter user reactions to a new-launched product. Another study by Rohman et al. (2020) conducted sentiment analysis on product reviews in a marketplace and combined it with Naive Bayes and K-NN algorithms. Han & Moghaddam (2021) also conducted research using sentiment analysis to efficiently identify individual user sentiments to relevant product attributes. Recent study we found is by Gozuacik et al. (2021), they also involved sentiment analysis to specifically analyze the Google Glass product, which considered to have failed in its marketing target. They were using data from tweets on the social media platform Twitter.

Another NLP approach that has been used to process customer reviews is ‘aspect detection’, as conducted in the study by Mokadam & Suresh (2020). They conducted this research to examine aspect detection as an important step in qualitative analysis of customer reviews. Aspect detection in NLP is process to identify and extract the main aspects or features from a text. These refer to specific elements that are the focus in the text, such as product attributes, topics discussion, or specific categories written in a review.

With the help of NLP, customer reviews can be effieciently extracted to know which product features are the concern to customers. We found that this began with Shamim et al. (2014), who used NLP to identify critical features from a large volume of customer reviews. Furthermore, Nikumanesh and Fathi (2017) proposed an innovative algorithm for extracting product features from online customer reviews and clustering these features into attribute groups based on expert opinions. Lin (2018) also conducted research
with the aim of understanding customer purchasing habits and identifying critical features of a product. Cataltas et al. (2020) proposed a text analysis method to identify product defect features by detecting features that indicate a tendency towards negative opinions in grouped customer reviews. In addition to manufacturing products, this technology can also be applied in the service industry, as demonstrated by the study conducted by Li et al. (2015), who used Emerging Pattern Mining techniques to identify new features that could attract the attention of international tourists.

The advancement in NLP also enables researchers to examine the emotions expressed in customer writings. Ullah et al. (2016) proposed the analysis of emotional content in a large dataset of online product reviews using NLP methods. The aim of this research was to contribute to the limited number of studies at that time that considered emotional factors. A recent related study was conducted by Zhou et al. (2010). This study introduced the Neural Personal Discrimination method, which is a breakthrough in learning the emotions conveyed in a text that are linked to personal attributes of customers.

Liu et al. (2019) conducted a demonstration on predicting customer purchasing behavior based on psychographic segmentation (psychological characteristics, behavior, and preferences of customers). They claimed that their research was the first to incorporate these factors in predicting customer behavior. Another study involving the personal attributes of customers is the research by Lai et al. (2019). In this study, dynamic internet data, including product reviews, user attributes, and product configurations, were used to analyze product design needs. In the same year, Hou et al. proposed a method to identify words and expressions related to what customers like and dislike in their written product reviews. A similar study involving dynamic data was conducted by Sun et al. (2020). In their previous research in 2019, Hou et al. introduced an approach to capture changes in user expectations regarding product capabilities by analyzing online reviews of two generations of products. A case study conducted on the Kindle e-reader, using reviews from amazon.com, demonstrated how designers can use this approach to evaluate product improvement strategies for previous iterations and develop new strategies for future products.

Competitor analysis based on user reviews can also be performed with the help of NLP. For example RE-SWOT created by Dalpiaz & Parente (2019), is a method used to gather requirements from app store reviews using competitor analysis. RE-SWOT combines NLP algorithms with information visualization techniques. The idea is comparing the reviews of own product with corresponding compepitor's product.

Therefore, in order to analyze customers' feedback, studies conducted by researchers have provided valuable contributions to the development of better understanding to customer needs. By leveraging NLP and also combining it with other approaches, companies can maximize their potential to understand customers' expectations and disires and can be able to provide successful products that meet customer satisfaction.

Non-VOC-related Studies

NLP can also be used to play a role in processes that do not involve customer opinions. We found that NLP has been used to assist in the new NPD process long before the era of social media as today.

At first, NLP was primarily used to obtain informations from a product design. The oldest research found was research 2001, when Prabhu et al. proposed a method for extracting geometric and non-geometric information from technical drawings that are created by using computer-aided design and drafting (CADD) tools. Several years later, we found Lv et al. (2005) have developed a web-based design variation knowledge management system for product design in Mandarin language texts. In 2011, Dabbish et al. utilized NLP to develop a semi-automatic method for extracting relationships between components in complex engineering projects by mining transcripts from discussions of its design.

We found that the most popular use of NLP in product development is to identify the requirements needed for NPD. Christophe et al. (2014) proposed a methodology to obtain and refine initial requirements in NPD. Elicitation was done by gathering supporting information from various sources such as patent databases, encyclopedias, and commercial websites. Qie et al. (2018) proposed an Artificial Intelligence-based framework to automatically analyze requirements and generate related models to enhance the efficiency and quality of the product development process. Zichler & Helke (2019) introduced a novel method that automatically converts unstructured or differently structured Customer Requirement Specifications (CRS) from Original Equipment Manufacturers (OEMs) into a structured language compatible with suppliers. Horber et al. (2020) introduced a new approach to connecting requirement models and evaluation criteria to address issues where overlooked requirements can lead to wrong decisions. Lastly, Schweitzer et al. (2021) conducted research where they created a framework to uncover AI requirements in virtual product development and applied NLP to enhance market knowledge and support automated development processes.

In recent years, NLP has also been used to process Engineering Change Request (ECR) documents. In 2020, Riesener et al. proposed a method for classifying ECR documents, and research by Pan and Stark developed a method to predict the components of a product that will be affected based on ECRs. Then Arnarsson et al. (2021) developed a method to search similarities and clustering on a database of ECR documents.

Through the utilization of NLP, researchers have conducted studies with purpose to adress existing problems in NPD. The first example is addressing language differences problem in international product development. Wen et al. (2013) have attempted to solve this problem, where they introduced the Cross-Language Transformation based on the Recursive Object Model (CLT-ROM). Furthermore, NLP can be utilized in idea-screening process, as demonstrated in the research by Guo et al. (2014). NLP can also help to gather expert knowledge from relevant documents, as proposed by Madhusadanan et al. (2017). NLP is also utilized in investigating various disruptions that may occur in a project and analyzing their impact on completion time, as explored by Abad et al. (2017). Additionally, it can be utilized in patent mining to extract information from patents, as demonstrated by Kim et al. (2018). Next, NLP can also be used for controlling the negative effects of product complexity, this was demonstrated by Wang et al. (2021), and Kleiza et al. (2016) NLP developing search tools that eliminate the need for users to be familiar with specific repositories and their details.

The uses of NLP in NPD that are unrelated to customer reviews are leveraged by applying NLP techniques, with purposes to analyze and understand texts related to the product, such as

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

requirement documents, ECR, drawings of product design, market research result, and any other information. NLP is used to extract information from text, identify trends and patterns in text. By leveraging NLP, product development team can optimize data collection processes, enhance understanding of user needs, and improve overall efficiency and quality in product development.

Roles of NLP in NPD

Natural Language Processing (NLP) plays a significant role in the process of New Product Development (NPD), especially in the current era of Big Data. In this section, we explore our findings regarding to the research question, which focuses on the specific parts of NPD where NLP has been utilized and the role of NLP in those particular areas.

The very important role of NLP today, which has been frequently used, is to understand customer needs. The availability of online customer reviews on a large-scale online marketplace provides valuable data for companies to capture customer responses to their products. In this regard, NLP clearly plays a role in the postlaunch evaluation process, where companies evaluate the products they have launched. Additionally, NLP can also assist in the process of generating new product ideas. By analyzing text from various sources such as journals, articles, or discussion platforms, NLP can help to identify trends, product defects, or innovative ideas that can serve as information for a NPD. We found one specific research that aims to discover new ideas. This was a research conducted by Li et al (2015). Then, for stage after 'idea generation stage', which is the 'screening stage' of the regenerated ideas, we found a study by Guo et al. (2014) that focused to assist in this stage.

By using similar approach explained before, NLP can also assist in other stages of product development that also directly uses customer opinions data, such as Concept Testing and Market Testing. The process of developing new product may be various between companies. Therefore, companies that conduct concept testing and market testing in their NPD process to gather market feedback can apply the same approach to analyze the customer feedback they receive.

As explained in previous section, NLP also plays a role in NPD stages that do not directly involve customer opinions. The majority of NLP applications in this purpose are used in the 'product development' stage, where product is being designed and then manufactured. In these stages, NLP is used to assist for understanding the design of a product, processing documents, and simplifying complex product.

Furthermore, NLP helps the process of information extraction. NLP can be used to extract important information such as desired product features, addresing issues that may be happened in NPD process, gathering expert knowledge, and extract the requirements in the production process stage. The power of NLP for doing these tasks can assist in the 'concept development' stage.

Theoretical and practical implications

Based on the discussion presented, in theory, NLP can help better understand customer preferences by analyzing textual data such as customer reviews or feedback from social media. By doing so, companies can more effectively identify customer preferences. In the future, various approaches and techniques will continue to be developed to better understand complex customer reviews, as suggested by Gozuacik et al. (2021). Dynamic data processing, as explored by Lai et al. (2019), also holds potential as user engagement rapidly increases. A practical implication for the future is the implementation of real-time monitoring systems to gather VOC, analyze trends, and conduct competitor analysis.

The implications of using NLP in each stage of NPD, specifically beyond VOC analysis, are still broad and depend on the specific area being developed. For example, in the context of document clustering, Arnarsson et al. (2021) suggest that in the future, their NLP techniques can be further developed to be applicable to a wider range of databases and process other types of data, such as numerical data, for document clustering purposes.

Conclusion

In order to provide satisfying products, every business must understand the needs and desires of their customers. In this era, computer technology has been utilized to assist in the New Product Development (NPD) process. Natural Language Processing (NLP) is technology that give computer ability to process human language, has frequently used in the process of developing new products.

By leveraging NLP, companies can understand a large number of customer reviews more quickly and easily. Because NLP can be used to extract important keywords from customer reviews, identify the aspects/topics that are discussed by customers in their reviews. Then, NLP can also be used to determine customer sentiment and emotions in their reviews.

Besides that, NLP has also been used in NPD stages that are not involving customers. NLP can be applied for processing Engineering Change Request (ECR) documents. It also utilized to identify the requirements needed in product design. Even before the era of social media and online marketplaces that provide online Voice of Customer (VOC) data as we do today, NLP was already employed in these tasks.

In the future, possible research studies could involve collecting Voice of Customer (VOC) data in the form of images or videos. This suggestion is based on the rapid development of social media platforms where internet users share visual content such as images and videos on platforms like YouTube, Instagram, TikTok, and others. It is not uncommon for users to share content in the form of their reactions to a newly purchased product or provide product reviews in video format. The advancements in Artificial Intelligence (AI) technology that can automatically generate transcripts from audio media can be utilized in this concept. AI's ability to detect human faces, expressions displayed, and even microfacial motions can also be linked to the emotions of content creators when speaking in the video.

List of References

Abad, Z. S. H., Ruhe, G., & Bauer, M. (2017). Understanding Task Interruptions in Service Oriented Software Development Projects: An Exploratory Study. *Proceedings - 2017 IEEE/ACM 4th International Workshop on Software Engineering Research and Industrial Practice, SER and IP 2017*, 34-40.

Aguwa, C., Olya, M. H., & Monplaisir, L. (2017). Modeling of Fuzzy-based Voice of Customer for Business Decision Analytics. *Knowledge-Based Systems*, 125, 136-145.

Akella, K., Venkatachalam, N., Gokul, K., Choi, K., & Tyakal, R. (2017). Gain Customer Insights Using NLP Techniques. *SAE International Journal of Materials and Manufacturing*, 10(3).

Arnarsson, I. Ö., Frost, O., Gustavsson, E., Jirstrand, M., & Malmqvist, J. (2021). Natural Language Processing Methods for Knowledge Management—Applying Document Clustering for Fast Search and Grouping of Engineering Documents. *Concurrent Engineering Research and Applications*, 29(2), 142-152.

Arnarsson, I. Ö., Frost, O., Gustavsson, E., Stenholm, D., Jirstrand, M., & Malmqvist, J. (2019). Supporting Knowledge Re-use with Effective Searches of Related Engineering Documents - A Comparison of Search Engine and Natural Language Processing-Based Algorithms. *Proceedings of the International Conference on Engineering Design*, 2019-August, 2597-2606.

Cataltas, M., Dogramaci, S., Yumusak, S., & Oztoprak, K. (2020). Extraction of Product Defects and Opinions from Customer Reviews by Using Text Clustering and Sentiment Analysis. *Proceedings - 2020 IEEE International Conference on Big Data, (Big Data 2020)*, 4529-4534.

Chen, X., Chen, C.-H., Leong, K. F., & Jiang, X. (2013). An Ontology Learning System for Customer Needs Representation in Product Development. *International Journal of Advanced Manufacturing Technology*, 67(1-4), 441-453.

Choi, J., Yoon, J., Chung, J., Coh, B. Y., & Lee, J. M. (2020). Social Media Analytics and Business Intelligence Research: A Systematic Review. *Information Processing and Management*, 25, 1-16.

Christophe, F., Mokammel, F., Coatanéa, E., Nguyen, A., Bakhouya, M., & Bernard, A. (2014). A Methodology Supporting Syntactic, Lexical and Semantic Clarification of Requirements in Systems Engineering. *International Journal of Product Development*, 19(4), 173-190.

Chunawalla, S. A. (2008). Product Management. Global Media.

Dabbish, L., Towne, B., Diesner, J., & Herbsleb, J. (2011). Construction of Association Networks from Communication in Teams Working on Complex Projects. *Statistical Analysis and Data Mining*, 4(5), 547-563.

Dalpiaz, F., & Parente, M. (2019). RE-SWOT: From User Feedback to Requirements via

Competitor Analysis. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11412 LNCS, 55-70.

Gozuacik, N., Sakar, C. O., & Ozcan, S. (2021). Social Media-based Opinion Retrieval for Product Analysis Using Multi-task Deep Neural Networks. *Expert Systems with Applications*, 183, 1-13.

Guo, G., Li, H., & Zhou, J. (2013). Customer Unstructured Requirement Analysis Based on Word Semantics and Metaphor Logical Techniques. *Zhongguo Jixie Gongcheng/China Mechanical Engineering*, 24(8), 995-1000.

Guo, W.-T., & Huynh, V.-N. (2014). A New Version of 2-Tuple Fuzzy Linguistic Screening Evaluation Model in New Product Development. *IEEE International Conference on Industrial Engineering and Engineering Management*, 164-169.

Gürbüz, E. (2018). Theory of New Product Development and Its Applications. *IntechOpen*, 7-74.

Han, Y., & Moghaddam, M. (2021). Analysis of Sentiment Expressions for User-centered Design. *Expert Systems With Applications*, 171, 1-11.

Horber, D., Schleich, B., & Wartzack, S. (2020). Conceptual Model for (Semi-) Automated Derivation of Evaluation Criteria in Requirements Modelling. *Proceedings of the Design Society: DESIGN Conference*, 1, 937-946.

Hou, T., Yannou, B., Leroy, Y., & Poirson, E. (2019). Mining customer product reviews for product development: A summarization process. *Expert Systems with Applications*, 132, 141-150.

Ittoo, A., & Bouma, G. (2013). Term Extraction from Sparse, Ungrammatical Domain-Specific Documents. *Expert Systems with Applications*, 40(7), 2530-2540.

Kim, H., Joung, J., & Kim, K. (2018). Semi-automatic Extraction of Technological Causality from Patents. *Computers and Industrial Engineering*, 115, 532-542.

Kleiza, K., Klein, P., Franke, M., & Thoben, K.-D. (2016). Integrated Semantic Search in the Product Development Phase. *2010 IEEE International Technology Management Conference*, ICE 2010.

Lai, X., Zhang, Q., Chen, Q., Huang, Y., Mao, N., & Liu, J. (2019). The Analytics of Product-Design Requirements Using Dynamic Internet Data: Application to Chinese Smartphone Market. *International Journal of Production Research*, 57(18), 5660-5684.

Li, G., Law, R., Vu, H. Q., Rong, J., & Zhao, X. (2015). Identifying Emerging Hotel Preferences Using Emerging Pattern Mining Technique. *Tourism Management*, 46, 311-321.

Lin, K.-Y. (2018). A Text Mining Approach to Capture User Experience for New Product Development. *International Journal of Industrial Engineering: Theory Applications and Practice*, 25(1), 108-121.

Liu, H., Huang, Y., Wang, Z., Liu, K., Hu, X., & Wang, W. (2019). Personality or value: A Comparative Study of Psychographic Segmentation Based on an Online Review Enhanced Recommender System. *Applied Sciences (Switzerland)*, 9(10), 1992.

Lovaglia, M. J. (1991). Predicting Citations to Journal Articles: The Ideal Number of References. *The American Sociologist*, 22(1), 49–64.

Lv, W., Lin, F., Wang, W., & Guo, B. (2005). Web-based Knowledge Reuse in Product Design. *ISCIT 2005 - International Symposium on Communications and Information Technologies 2005, Proceedings*, I, 1056-1059.

Madhusudanan, N., Gurumoorthy, B., & Chakrabarti, A. (2017). Automatic Expert Knowledge Acquisition from Text for Closing the Knowledge Loop in PLM. *International Journal of Product Lifecycle Management*, 10(4), 301-325.

Mokadam, A., & Suresh, M. A. (2020). DoSSAD - Leveraging Domain Specific Semantics in Aspect Detection for Product Design. *IEEE 14th International Conference on Semantic Computing*, 249-252.

Nikumanesh, E., & Fathi, M. (2017). An Indicator for Measuring Sentiment and Polarity: Applied Knowledge Discovery Using Online Customer Reviews. *IEEE International Conference on Electro Information Technology*, 472-475.

Pan, Y., & Stark, R. (2020). An Ensemble Learning based Hierarchical Multi-label Classification Approach to Identify Impacts of Engineering Changes. *Proceedings -*

International Conference on Tools with Artificial Intelligence, ICTAI, 2020-November, 1260-1267.

Prabhu, B. S., Biswas, S., & Pande, S. S. (2001). Intelligent System for Extraction of Product *Data from CADD Models. Computers in Industry*, 44(1), 79-95.

Qie, Y., Zhu, W., Liu, A., Zhang, Y., Wang, J., Li, T., Li, Y., Ge, Y., & Wang, Y. (2018). A Deep Learning Based Framework for Textual Requirement Analysis and Model Generation. *2018 IEEE CSAA Guidance, Navigation and Control Conference, (CGNCC 2018).*

Ramaswamy, S., & DeClerck, N. (2018). Customer Perception Analysis Using Deep Learning and NLP. *Procedia Computer Science*, 140, 170-178.

Ramdhani, A., Abdullah, M. A., & Amin, S. A. (2014). Writing a Literature Review Research Paper: A step-by-step approach. *International Journal of Basic and Applied Science*, 3, 47-56.

Rathore, A. K., & Ilavarasan, P. V. (2017). Social Media Analytics for New Product Development: Case of a Pizza. *International Conference on Advances in Mechanical, Industrial, Automation and Management Systems*, 213-219.

Riesener, M., Dölle, C., Mendl-Heinisch, M., Schuh, G., & Keuper, A. (2020). Derivation of Description Features for Engineering Change Request by Aid of Latent Dirichlet Allocation. *Proceedings of the Design Society: DESIGN Conference*, 1, 697-706.

Rohman, A. N., Luviana Musyarofah, R., Utami, E. R., & Raharjo, S. (2020). Natural Language Processing on Marketplace Product Review Sentiment Analysis. *2020 2nd International Conference on Cybernetics and Intelligent System (ICORIS 2020).*

Schweitzer, G. M., Bitzer, M., & Vielhaber, M. (2021). Artificial Intelligence in Engineering: Evolution of Virtual Product Development in the Context of the Medical Device Industry. *Procedia CIRP*, 100, 349-354.

Shamim, A., Balakrishnan, V., Tahir, M., & Shiraz, M. (2014). Critical Product Features' Identification Using an Opinion Analyzer. *Scientific World Journal*, 2014, 340583.

Sun, H., Guo, W., Shao, H., & Rong, B. (2020). Dynamical Mining of Ever-Changing User Requirements: A Product Design and Improvement Perspective. *Advanced Engineering Informatics*, 46, 101174.

Tezuka, T., & Tanaka, K. (2005). Landmark Extraction: A Web Mining Approach. *Springer-Verlag Berlin Heidelberg* (pp. 379-396).

Timoshenko, A., & Hauser, J. R. (2019). Identifying Customer Needs from User-generated Content. *Marketing Science*, 38(1), 1-20.

Trott, P. (2017). *Innovation Management and New Product Development* (6th ed.). Pearson Education Limited, Edinburgh Gate (pp. 498-499).

Tzokas, N., Hultink, E. J., & Hart, S. (2004). Navigating the New Product Development Process. *Industrial Marketing Management*, 33(7), 619-626.

Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From Valence to Emotions: Exploring the Distribution of Emotions in Online Product Reviews. *Decision Support Systems*, 81, 41-53.

Wang, K., Tan, R., Peng, Q., Wang, F., Shao, P., & Gao, Z. (2021). A Holistic Method of Complex Product Development Based on a Neural Network-aided Technological Evolution System. *Advanced Engineering Informatics*, 48, 101294.

Wen, K., Tan, S., Wang, J., Li, R., & Gao, Y. (2013). A Model-Based Transformation Paradigm for Cross-Language Collaborations. *Advanced Engineering Informatics*, 27(1), 27-37.

Zhou, X., Wang, Z., Li, S., Zhou, G., & Zhang, M. (2020). Emotion Detection with Neural Personal Discrimination. *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing*.

Zichler, K., & Helke, S. (2019). R2BC: Tool-Based Requirements Preparation for Delta Analyses by Conversion into Boilerplates. *CEUR Workshop Proceedings*.

DOI: https://doi.org/10.26593/jrsi.v13i1.6790.117-130

This page is intentionally left blank.