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Transfer-Learning-Based Opinion Mining for New-Product Portfolio Configuration over the Case-Based Reasoning Cycle

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Abstract: Due to the ever-changing business environment, enterprises are facing unprecedented challenges in their new-product development (NPD) processes, while the success and survival of NPD projects have become increasingly challenging in recent years. Thus, most enterprises are eager to revamp existing NPD processes so as to enhance the likelihood of new products succeeding in the market. In addition to the determination of sustainable new-product ideas and designs, new-product portfolio management (NPPM) is an active research area for allocating adequate resources to boost project development, while projects that perform poorly can be terminated. Since the existing new-product portfolio configuration is manually decided, this study explores the possibility of standardising NPPM, particularly the configuration mechanism, in a systematic manner. Subsequently, case-based reasoning can be applied to structure the entire NPPM process, in which past knowledge and successful cases can be used to configure new projects. Furthermore, customer feedback was analyzed using the transfer-learning-based text classification model in the case-retrieval process to balance the values of enterprises and customers. A new-product portfolio was therefore configured to facilitate NPPM under an agile–stage-gate model. To verify the effectiveness of the proposed system, a case study in a printer manufacturing company was conducted, where positive feedback and performances were found.

Keywords: new product development; portfolio management; case-based reasoning; transfer learning; text classification

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1. Introduction

In recent years, due to the presence of several major supply chain disruptions leading to shortages of electronic components—for example, the COVID-19 pandemic and Russia–Ukraine war—new-product development (NPD) in industry has become unprecedentedly challenging regarding the development of successful new products for customers. Customer value and satisfaction are difficult to maintain, not to mention improvements in the current NPD process. To develop successful new products, some existing studies revealed that new-product ideas should be selected in a systematic and group-based manner, while product portfolios can be effectively formulated to address customer and technical needs [1,2]. In the context of NPD research, the theory of new-product portfolio management (NPPM) has been widely discussed to measure, evaluate, and manage NPD projects [3]. In addition, decisions regarding continuation, termination, and prioritization can be made to strike a reasonable balance between manufacturers, customers, and other stakeholders. The effectiveness of NPPM can influence key performance aspects of new products launched in the market, such as production cycle time, human resources, and budget. Therefore, there is an urgent need for industrial practitioners to develop a systematic approach for the formulation of the most appropriate and reasonable product portfolios, enhancing the likelihood of new-product survival and success in the market. As the saying goes, "prevention is always better than cure", so the new-product portfolios should be configured with the most reasonable settings at the beginning, rather than making modifications and cancellations after NPD. However, the current configurations of NPPM suffer from two pitfalls. First, the current new-product portfolios are configured on a company-driven basis, such that the product manufacturers have the sole privilege of creating the product and project specifications, regardless of the customers' perspectives. Additionally, customer feedback is seldom considered in the portfolio configuration process. Moreover, the appropriate design of intelligent systems in assisting portfolio configuration is currently limited in industry. Although modern advances in artificial intelligence and machine learning in industrial design are significant [4], intelligent portfolio management is still a valuable but understudied area due to the lack of sample-rich datasets to train and validate machine-learning models.

To address the above challenges in the context of NPPM, this study presents an intelligent new-product portfolio configuration system (INPPCS), where case-based reasoning (CBR) and transfer learning are hybridized to suggest the most appropriate portfolio configurations for the development of new products. More importantly, customers' reviews and feedback were extracted and analyzed to derive the weights of the portfolio management criteria. Thus, customers are involved in determining the most similar case retrievals in the CBR cycle, so the retrieved cases can serve as references to support the development of a new-product portfolio. In order to effectively understand customers' needs, the transfer-learning approach is adopted to perform a review classification through fine-tuning the pre-trained bidirectional encoder representations from transformers (BERT). Therefore, the classification performance can be maintained to a reasonable degree, even if the dataset is relatively small. Such a systematic design can effectively satisfy the needs of NPPM, when the size of customers' comments on specific new products are relatively small. To further verify the feasibility of the proposed system, a case study of a printer manufacturer located in China was undertaken, in which the manufacturer was eager to design and develop new printing equipment and services for their customers. It was found that historical product portfolios can be extracted to support new-product portfolio configuration, with positive feedback from the manufacturer's and customers' perspectives.

The major contributions of this study can be summarized in two areas. First, from the technical aspect, the case-adaptation mechanism in the CBR cycle is revamped by the transfer-learning approach. To be specific, the attribute weights in the case-similarity evaluation function can be determined through analyzing customer reviews relevant to new products. Thus, the most similar case can be identified to support the formulation of the new-product portfolio. Second, due to the incorporation of customer reviews in the case-adaptation process, NPPM is shaped in a customer-driven manner to consider customer thoughts and perceptions, and the new-product portfolio can, therefore, be designed to satisfy not only the manufacturers' needs, but also customer requirements. Consequently, the likelihood of new-product success in the currently ever-changing business environment can be increased.

The remainder of this paper is organized as follows. In Section 2, a literature review related to (i) new-product portfolio management and (ii) intelligent portfolio management approaches is presented, which identified the gaps in exploiting transfer learning in the CBR mechanism. In Section 3, the research methodology, namely the proposed architecture of the INPPCS, is presented, where the transfer-learning-based CBR mechanism is developed. In Section 4, the proposed system is implemented in a case study of a company to verify its feasibility and performance. In Section 5, the findings and managerial insights into NPPM are discussed. Finally, the conclusions and potential directions for future studies are presented in Section 6.

2. Literature Review

In this section, the theory of NPPM is reviewed to outline the essential concepts and components for achieving new-product success. To standardize and computerize NPPM, existing intelligent solutions are also summarized to show the research gaps in this study area.

2.1. Portfolio Management in New-Product Development

Starting from the 1990s, the concept of new-product portfolio management (NPPM) was raised to drive innovation and business success [5]. It is a company-driven process to select the right new-product ideas for design and development phases, with appropriate resource allocation, in order to achieve successful product innovation in the market. In short, NPPM was defined as follows: "Portfolio management is a dynamic decision process, whereby a business's list of active new product (and R&D) projects is constantly updated and revised. In this process, new projects are evaluated, selected, and prioritized; existing projects may be accelerated, killed, or deprioritized; and resources are allocated and reallocated to the active projects". The decision-making problems related to NPPM have been widely discussed to examine managers' perspectives and to formulate computational frameworks to balance project value and strategic fit [6,7]. Because the business environment and market are ever-changing and sensitive to supply-chain disruptions, the conversion from innovation strategies into investment decisions under NPPM has been facing two major challenges in recent years: (i) the difficulty to concurrently manage a great number of development projects, and (ii) the poor data integrity of NPD projects [3]. To address these active challenges, the traditional stage-gate model was refined with an agile methodology in order to construct an agile–stage-gate model. Compared with the traditional stage-gate model, the agile–stage-gate model abandons conventional project management approaches, such as Gantt charts and critical plan planning. Instead, a series of time-boxed iterations were configured to make the go/kill decisions of the projects by measuring their actual outcomes. Such an agile approach can evaluate NPD projects in a dynamic manner, while poorly performing projects can be spotted and immediately terminated. Although the novel agile–stage-gate model can address the existing challenges of the traditional stage-gate model, the most crucial process in NPPM is the first step—configuring the new-product portfolio to estimate its production cycle time, budget, and human resources. Incorrect estimations can result in insufficient resources and expectations for new products [8]. Moreover, the agile–stage-gate model can be applied in the field of product development [3,9,10]; therefore, iterative cycles and external collaborations can be incorporated into contemporary product-development processes. A flexible NPD process can also be established to adapt to the ever-changing market trends and business requirements. Thus, potential new-product ideas can be ruined due to an inappropriate new-product portfolio configuration [11]. In view of this, computerized and intelligent approaches for configuring the new-product portfolio need to be further explored.

2.2. Intelligent Methods for Portfolio Configuration and Management

In the era of Industry 4.0, a number of advanced technologies and methods—for example, artificial intelligence, big data, and the industrial internet of things—are well-established for enhancing industrial intelligence, leading to the digital transformation of NPD activities [12,13]. Among various artificial intelligence techniques, case-based reasoning (CBR) is a promising methodology to build project portfolios and plans based on a knowledge repository of historical cases of [14]. Moreover, the cost-estimation mechanism can be embedded to predict NPD budgets for specific project portfolios. Liu et al. [15] stated that new-product designs were inspired by existing designs in the past and, therefore, similar designs from the past should be re-used to facilitate the NPD process. Subsequently, CBR was integrated with fuzzy relational analysis, and C-K theory was exploited to adapt historical designs for creative design. Design knowledge can be systematically retained and managed through the use of CBR. Alternatively, some studies investigated the problem of new-product portfolio selection to facilitate planning the number of units per variant allocated in a given period, where the multi-objective tabu search algorithm can be applied accordingly [16]. Effective product portfolio selection is essential to reduce the perceived risks in the supply chain and manufacturing processes [17]. However, existing product portfolio management is solely developed from manufacturers' perspectives, regardless of customer involvement. The manufacturers are responsible for designing, planning, and developing new products for customers who cannot participate in the project planning stage. Therefore, cognitive solutions for NPD should be explored [18], as it is likely that the final products after mass production might not be launched at the right time or with the right quality and quantity.

2.3. Summary of the Literature Review

In summary, new-product portfolio management is one of the actively explored theories in the context of NPD research seeking to increase the survival of new-product ideas in the market. Moreover, the go/kill decisions of new-product ideas can efficiently minimize the loss of company resources and maximize the value of new products. In addition to iterative assessments of NPD projects, initial project configuration is essential to assign adequate talent and resources to cultivate valuable new-product ideas. It is commonly believed that the assignment of adequate resources and talents may increase the likelihood of new-product survival in a challenging business environment. In the enhancement of project portfolio configuration, CBR is a promising tool to review and adapt historical cases so as to formulate new portfolio configurations for new-product ideas. According to existing studies in the field of new-product portfolio management [19,20], customer requirements are essential for effective portfolio configuration and management, but the data source of customer feedback from online retail platforms is seldom discussed in the existing literature. Because the current case-adaptation mechanism highly relies on the manufacturers themselves, further research on exploring the customer-based case-adaptation mechanism is essential for case retrieval and reuse so that a project portfolio can be set up in a customer-oriented manner through leveraging the power of machine learning [21].

3. Research Methodology

The complete research methodology that addresses the challenges in NPPM consists of two main components: (i) preliminaries and (ii) the architecture of the INPPCS. In particular, the transfer-learning scheme is incorporated into the CBR mechanism to assist in the case-adaptation process. Compared with existing approaches [17,18], the proposed system leverages the power of case-based reasoning and transfer learning to configure new-product portfolios. Unlike other intuitive and manual approaches, a systematic approach can generate a new-product portfolio by referring to previous successful product portfolios. With the aid of the proposed system, the process of new-product portfolio management can be standardized to ensure the reliability and consistency of solutions.

3.1. Methodological Preliminaries

Regarding the preliminaries of the proposed INPPCS, two fundamental concepts are described in this section for integration in the development of the INPPCS: case-based reasoning and transfer learning.

3.1.1. Case-Based Reasoning for Portfolio Management

When the most suitable new-product ideas are determined, along with their forecasted demand, a comprehensive project portfolio can be formulated to structure NPD activities and launch new products in the market in a reasonable period of time. To formulate the project portfolio, the case-based reasoning (CBR) approach is applied [22], where a number of historical NPD projects are stored in the case library for supporting the new portfolio formulation. In general, there are four major steps in the closed-loop structure of the CBR: (i) retrieve, (ii) reuse, (iii) revise, and (iv) retain. To be specific, similar past portfolios of NPD projects are extracted from the case library according to the new-product types, where effective case-searching schemes should be developed to enhance the searching efficiency. A list of relevant cases from the case library can be extracted for similarity evaluation. For example, if a new home printing machine is going to be developed and produced, previous cases of home printing machines, instead of other commercial printers, should be considered.

Among the retrieved past cases, a similarity evaluation between the new NPD project and past projects is performed by considering the project attributes, such as the number of new components/modules in the new product. The similarity evaluation can be generally expressed as in Equation (1), where f_i^n and f_i^o represent the values of the attribute i for new and old cases, and w_i represents the weights of individual attributes. According to the similarity measurement, the historical cases/portfolios can be ranked to select the most similar case for further modification by domain experts, such as the managers and engineers in the NPD team. Subsequently, the new-product portfolio is established to guide the entire NPD activities. In other words, the NPD process can be started with a comprehensive project portfolio under the agile–stage-gate model. In addition to applying the modified project portfolio in practice, the successful cases are retained in the case library for future retrieval and, therefore, the project portfolio formulation process can be computerized with the easy benchmarking of historical cases so as to enhance the quality and comprehensiveness of NPD projects.

$$S_i = \frac{\sum_{i=1}^{n} w_i \cdot sim(f_i^n, f_i^o)}{\sum_{i=1}^{n} w_i}, \text{where } sim(f_i^n, f_i^o) = \frac{\min(|f_i^n|, |f_i^o|)}{\max(|f_i^n|, |f_i^o|)} \tag{1}$$

3.1.2. Transfer Learning for Natural Language Processing

In the recent literature, transfer learning, which has drawn considerable attention from academics and developers, has been used to solve existing problems, such as (i) insufficiently labeled data for training and (ii) expensive and time-consuming issues in model training and in supervised and semi-supervised learning [23]. The main objective of transfer learning is to generalize and transfer knowledge across different domains, where some of the tasks share common knowledge in reality. For instance, a person who can swim can learn how to dive faster than others, following the generalization theory of transfer. The general transfer-learning scheme is illustrated in Figure 1, where the knowledge obtained from a large and generalized dataset can be transferred to a local and domain-specific machine-learning model. Subsequently, this model can effectively perform domain-specific tasks with enhanced reliability and consistency, in which the likelihood of overfitting the machine-learning model can be reduced.

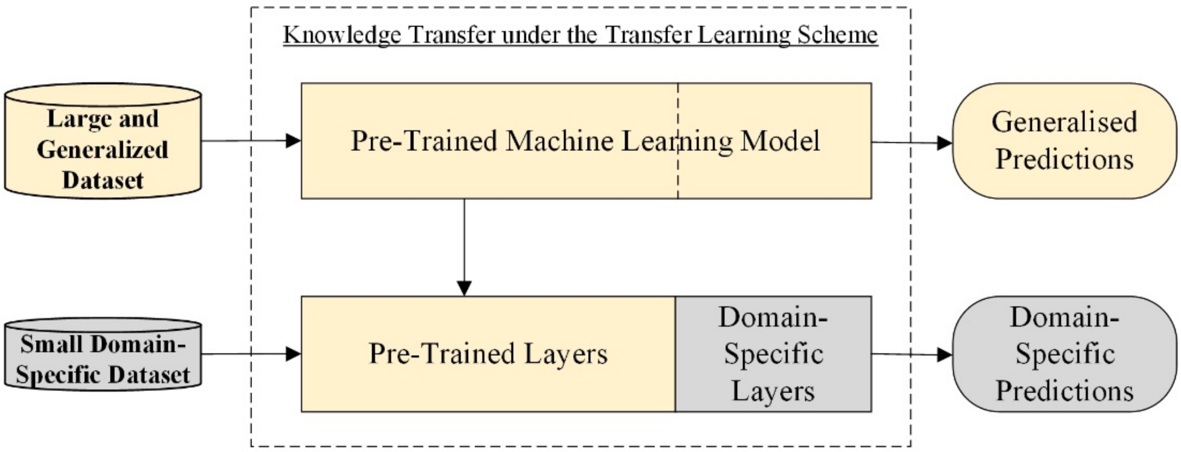

Figure 1. Generic illustration of the transfer-learning mechanism.

Recently, one of the active application areas of the transfer-learning scheme concerns text classification, where some pre-trained language models can be applied to shorten the time for model training. In the past, recurrent neural networks (RNNs) were explored in NLP research, but it was found that processing the input sequence token-by-token was relatively time-consuming. In our study, the transformer model developed by Google in December 2017 [24,25] was further used to perform the text classification. To achieve the above objectives, the pre-trained bidirectional encoder representations from transformers

(BERT) model was fine-tuned on a relatively small and domain-specific dataset by using a huge dataset on Wikipedia and Book Corpus with more than 3000 million words in total. In order to fine-tune the BERT model, there are some general approaches, including (i) training the entire model architecture on the pre-trained mode to feed the output to the Softmax layer, (ii) partially training higher layers from the model architecture, and (iii) freezing the entire model architecture by attaching a few additional layers. In cases of insufficient local datasets, a third approach was considered in our study to keep the entire BERT model unchanged during its fine-tuning. This approach is deemed to be effective for constructing various NLP applications, such as spam classification.

Mathematically, fine-tuning the BERT model can be used to perform the class prediction of a single sentence, with the class label C = $\{c_1, c_2, \ldots, c_n\}$ for the input sentence I = $\{i_1, i_2, \ldots, i_m\}$. Therefore, the probability that the sentence i_p is labeled as c_q can be expressed as Equation (2), where the logistic regression with Softmax can be applied. The value x denotes the contextual representation of the sentence for the text classification, and W^T_{SST-2} represents the task-specific parameter matrix.

$$\mathrm{P}\left(c_q \middle| i_p\right) = \mathrm{softmax}\left(W^T_{SST-2}.x\right) \tag{2}$$

To further illustrate the fine-tuning process of the BERT model for the purpose of a customized text classifier, Figure 2 shows the generic workflow of the entire fine-tuning process for building a customized text classifier based on the pre-trained BERT. At the pre-training phase, the BERT model is trained by using the BooksCorpus and English Wikipedia to formulate a generic binary text classifier, where generalized word representation is established to understand the linguistic information. In order to customize the BERT model for a specific application domain, a fine-tuning process is needed, in which a set of annotated datasets, such as customer feedback on online retail platforms, is applied to refine the BERT model. Consequently, the original binary text classifier can be customized to perform the classification task on customer feedback in terms of innovativeness and sustainability.

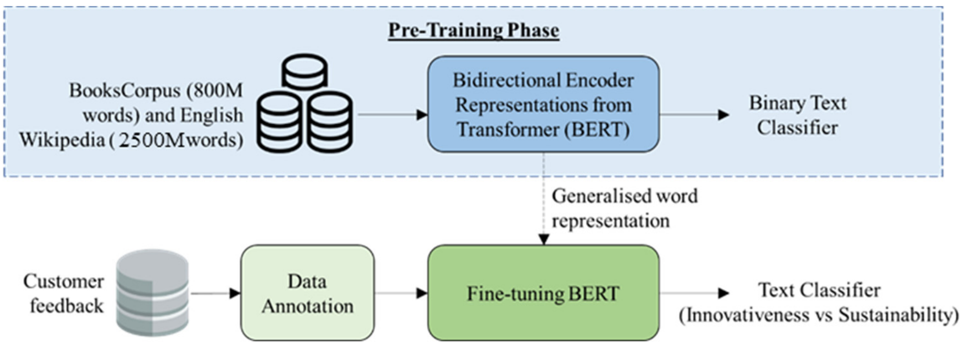

Figure 2. General process of fine-tuning BERT.

3.2. Architecture of the INPPCS

Through integrating the transfer-learning scheme and CBR, the proposed INPPCS can be built to suggest the new-product portfolios to NPD engineers/managers. Figure 3 presents the proposed architecture of the INPPCS with the incorporation of transfer learning in the case-adaptation process in the CBR cycle. In the proposed system, CBR is applied as the backbone for building new-product portfolios, while transfer learning plays the role of providing attribute weights for similarity measurements through analyzing customer reviews of specific products. To describe the entire architecture, case retrieval and adaptation are two major aspects used to build the new-product portfolios. All new-product ideas in the same category share the same set of product attributes, which can be further applied in the case-based reasoning mechanism. Therefore, a new-product portfolio can be generated by referring to previous successful and similar NPD projects, so as to enhance the products' success and survival rate in the market.

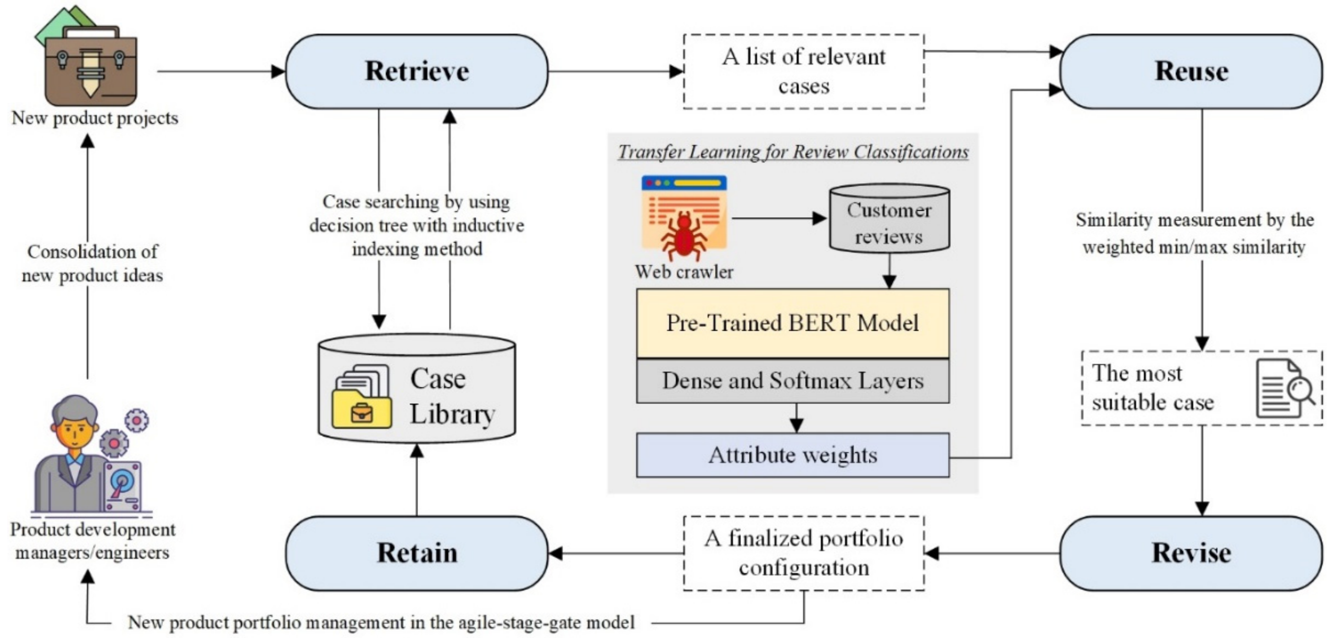

Figure 3. Architecture of the INPPCS.

In the case-retrieval process, concrete new-product ideas are consolidated by product development managers/engineers as new-product projects. First of all, to construct an effective project portfolio, historical cases relevant to the new-product projects are retrieved from the case library, where the decision tree using the inductive indexing method is applied to limit the searching space during the case-searching process. In view of this, a two-level decision tree for case indexing is built to retrieve a sub-class of cases, where two stopping conditions are applied: (i) if a project is developing a completely new product (yes or no), and (ii) the target industry of a new product (retail stores or logistics or office use). In addition to the relevance of the retrieved cases, the similarities between the NPD project and all relevant cases are evaluated using Equation (1), where the attribute weights are obtained using a transfer-learning-based approach. Table 1 contains eight attributes that are considered under two attribute classes. However, the weights between the two classes are not assumed to be equal and are determined by using the text classification from the online customer reviews about relevant products.

Table 1. Classes and attributes for the similarity evaluation.

Class	Class Name	Attributes
1	Innovativeness	• Print reliability and resolution (X_1, Scale: 1–5); • Paper cutter reliability (X_2, Scale: 1–5); • Print speed (X_3, Unit: mm/s); • Ease of consumable replacement (X_4, Scale: 1–5); • Port compatibility (X_5, Scale: 1–5).
2	Sustainability	• Expected life span (X_6, Unit: years); • Energy consumption (X_7, Unit: watt); • Trade-in value at the end-of-life span (X_8, Unit: RMB).

By using the web-crawling method, customer reviews of specific products from the retail e-commerce platforms can be collected as a corpus, where a series of pre-processing steps on textual data are performed, including tokenization, lemmatization, stemming, and stop-words removal. From all the customer reviews, a subset of the reviews was extracted and annotated to fine-tune the bidirectional encoder representations from transformers (BERT) model, while some meaningless and irrelevant comments, such as scam messages, were removed from the dataset. To be specific, the customer reviews are limited to the specific product categories, or even specific brands, and thus customer feedback is highly related to new-product ideas for building portfolios. With the use of the fine-tuned BERT, recent customer reviews on the relevant products can be classified into two pre-defined attribute classes, and thus the ratio between the two classes can be determined to support the similarity evaluation. The fine-tuning process for customizing the BERT model is conducted in the Python 3 environment, where Python libraries, including numpy, pandas, torch, sklearn, and transformers, are imported. In the BERT model, the transformer network was trained using a large set of unlabeled textual data, including Wikipedia and Book Corpus. Therefore, the model is capable of understanding textual meaning and synonyms to facilitate the customization of specific application domains. Consequently, the most suitable case can be identified to construct a new portfolio of the new products.

In the case-adaptation process, the most similar and suitable case is considered in order to build the project portfolio in terms of its production cycle, human resources, and project budgeting. For the production cycle, the timelines of four major phases, namely the engineering verification test (EVT), design verification text (DVT), production verification test (PVT), and mass production (MP), are specified. For the human resources, the assignment of an appropriate number of research staff, product engineering staff, and supportive staff is needed. Finally, for project budgeting, the costs related to NPD—for example, prototype development, mould development, trial runs of the production, and certificate applications (3C/ROHS/CE/FCC, etc.)—are determined. With the finalized new-product profile, the entire new-product portfolio management, together with other NPD projects, can be performed by the product-development managers/engineers. Last but not least, the new-product profile is also retained in the case library under the inductive indexing method for future retrieval and analysis.

4. Case Study

To verify the feasibility and performance of the proposed system, a case study was conducted to address the needs and motivation of the case company, where the entire new-product portfolio-configuration process was investigated.

4.1. Case Company and Its Motivations

The case company is called Gainscha. It was established in 1999. It is located in Zhuhai city in China, close to the casino city of Macao. The factory has 600 employees and a total floor space of 40,000 square meters, 15% of which is allocated for new-product development. It is a pioneering and professional enterprise in China's mini-printer industry, focusing on mid- to high-end barcode and receipt printer technology innovations, R&D, production, sales and services, and forward-looking R&D technology with a high development efficiency. Additionally, its systematic management is very important, improving customer service quality and becoming further developed in various industries and fields, striving to make products and establish an enterprise in order to achieve the world-leading market position. Although the case company has rich experience and expertise in NPD, a high reliance on domain experts to develop new products might involve a certain subjectivity and human biases. In addition, historical NPD cases cannot be utilized to support the future formulation of NPD projects in a systematic manner. Therefore, the case company is eager to develop an intelligent system to assist in new-product portfolio management; accordingly, NPD projects can be configurated in a systematic manner by referring to successful cases in the past. Specifically, the machine-learning mechanism can be embedded in NPD activities so as to reduce human reliance. Consequently, the performance of the NPD projects can be enhanced, with higher survival and success rates in the market.

4.2. Deployment of the INPPCS

For the deployment of the INPPCS in the case company, the implementation is composed of three phases: (i) data collection, (ii) case retrieval, and (iii) case adaptation.

Specifically, the web scraper, CBR engine, and transfer learning to fine-tune the BERT model for text classification are integrated into the aforementioned solution.

4.2.1. Phase 1: Data Collection

Regarding data collection, two types of data—historical cases and customer reviews—are collected. For the historical cases, the case company consolidates all of its previous NPD projects, which are managed in the case library. All cases are stored in the case library based on their index values for efficient case retrieval, while the case attributes are used to measure the similarity with other cases. From the case company, 30 cases were structured as above for retention in the case library for demonstration.

Regarding the collection of the customer reviews of printing equipment, the customer reviews on Amazon up to 27 May 2022 were extracted using a web scraper based on the python library of Beautiful Soup, and thus the review data can be pulled from the HTML pages. To simply demonstrate the proposed mechanism, three printing devices were considered with 89 customer review titles and bodies containing 10,129 words. Moreover, text pre-processing was conducted to tokenize the collected textual data for the text classification using transfer learning, in which stemming, lemmatization and stop-word removal were applied. Subsequently, only meaningful tokens were extracted for each customer review, such as the document in the corpus. In addition to fine-tuning the pre-trained BERT model, 50 customer reviews related to the case company's products were then classified to obtain the weightings between different classes.

4.2.2. Phase 2: Case Retrieval

To demonstrate the process of the new-product portfolio configuration, a new-product idea from the case company, a thermal receipt and label printer, was provided. Since the case company has a long development history of thermal label printers, the new-product idea is an innovation from the existing models, which incorporate novel features and functions, including compatibility with mobile devices on Android and iOS, autonomous label calibration, and durable design. Moreover, this new-product idea is designed for logistics companies to print shipment and inventory labels for warehousing and transportation operations. Consequently, based on the inductive indexing method, five relevant cases from the case library were extracted for the similarity evaluation in order to determine the most similar case as a reference. In order to effectively classify the selected customer reviews, the pre-trained BERT model was fine-tuned using the training dataset, for which the distribution of the length of reviews is shown in Figure 4. In addition, the learning rate and training epoch were set at 1×10^{-5} and 1000, respectively.

After performing 1000 training epochs, the pre-trained BERT model was then fine-tuned for the review classification so as to determine whether the customer reviews belonged to innovativeness or sustainability. Training and validation losses are illustrated in Figure 5; it was confirmed that BERT was effectively tuned for specific purposes. It was found that the fine-tuning process with the training and validation ratios [0.3, 0.5] were relatively effective for controlling the losses.

Afterwards, the review classification on the 50 selected reviews related to Gainscha's products could be performed with the weights [38/50, 12/50] = [0.76, 0.24]. Additionally, the attribute weights within the same class were assumed to be equal. Given the attribute weights, the similarity between the new-product idea and the existing five project portfolios could be measured, as shown in Table 2. It was found that the similarity value between the new case and HC2 was the highest, with a value of 0.8968. Therefore, HC2 was then retrieved to support the case-adaptation process.

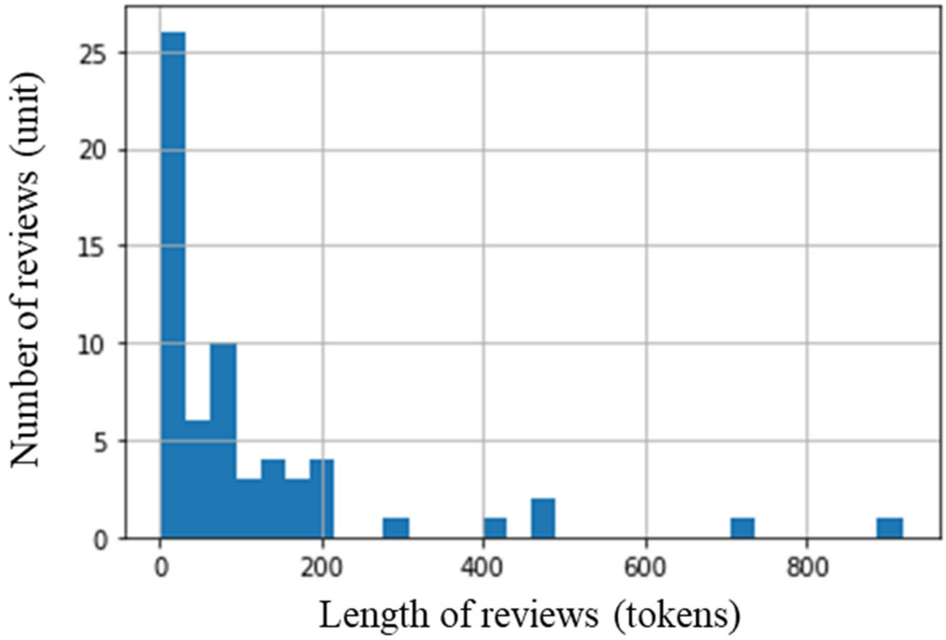

Figure 4. Distribution of the reviews from the training dataset.

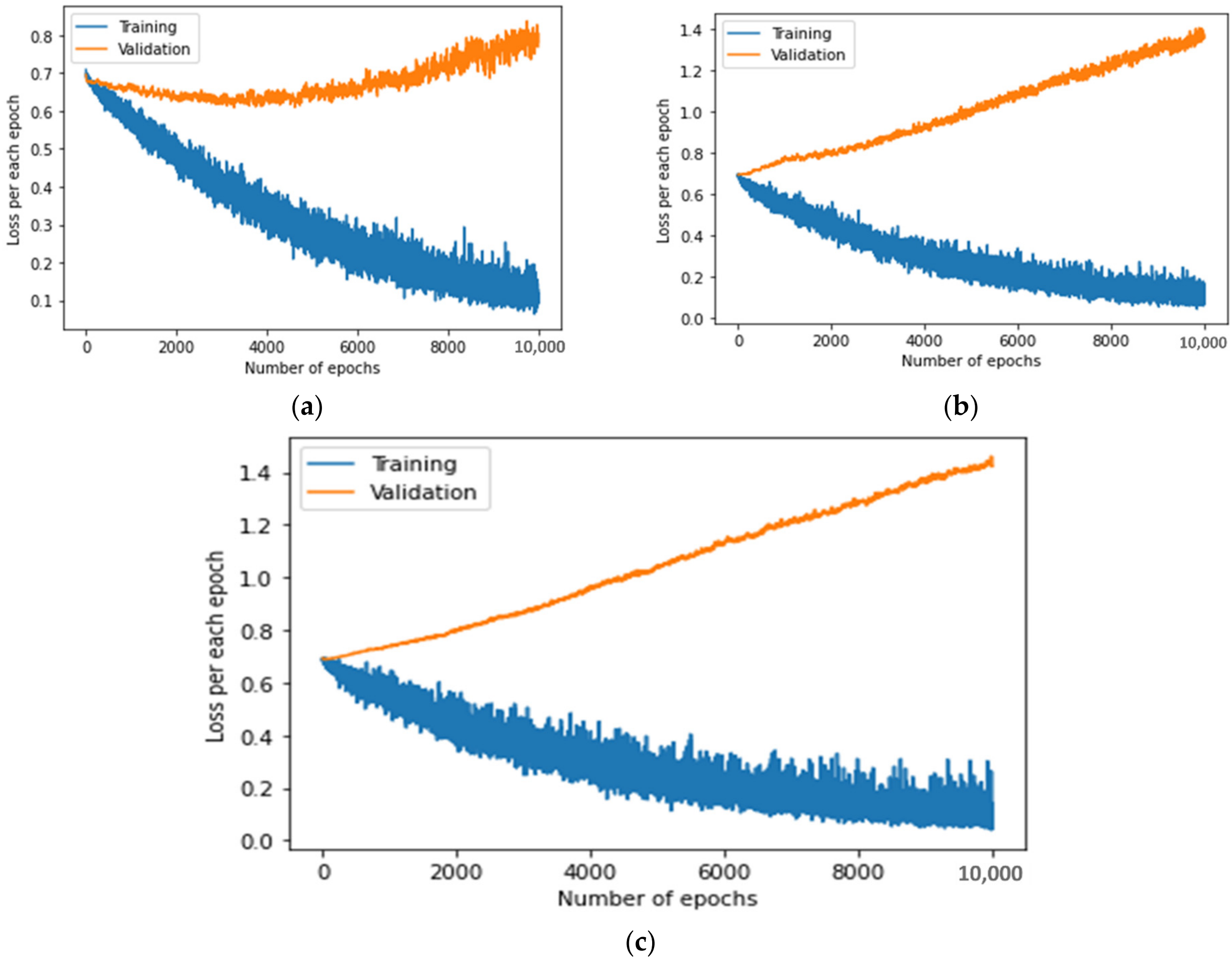

Figure 5. Training and validation losses over epochs. (**a**) [0.3, 0.5]. (**b**) [0.4, 0.4]. (**c**) [0.5, 0.3].

Table 2. Similarity evaluation between new case and historical cases.

Attribute	New Case	HC1	HC2	HC3	HC4	HC5
X_1	5	4	5	3	4	5
X_2	5	3	4	3	5	4
X_3	160	152	165	120	120	90
X_4	4	2	4	3	4	5
X_5	5	2	4	3	4	3
X_6	2	3	2.5	2	5	2.5
X_7	12	60	15	12	25	25
X_8	550	250	450	200	350	250
Similarity to new case:		0.6166	0.8968	0.6804	0.8119	0.7247

Remark: HC1 to HC5 denote the historical cases extracted from the case library.

4.2.3. Phase 3: Case Adaptation

By referring to HC2, the new-product portfolio for the new idea could be constructed, where the configurations of production planning, human resources, and budget could be benchmarked, as shown in Table 3. Although HC2 was the most similar case for building the new-product portfolio, there was some room to further improve the configuration of the new-product idea in order to increase the success and survival rates of the new product in the competitive market. NPD managers and engineers could revise HC2 based on engineering and customer requirements to estimate the appropriate setting for the new-product idea. Once the new-product portfolio configuration was formulated, this NPD project could be added into the portfolio management system to effectively monitor project development under the agile–stage-gate model. According to the agile–stage-gate model, the iterative process could monitor the projects so as to make the kill/go decisions at the right time. In addition to the practical value of the new-product portfolio configuration, the finalized portfolios were retained in the case library for future case retrieval in the CBR mechanism.

Table 3. New-product portfolio configuration of the new-product idea.

Aspect	Parameters	HC2	New Case
Index	Index 1	No	No
	Index 2	Logistics	Logistics
Attribute	X_1	5	5
	X_2	4	5
	X_3	165	160
	X_4	4	4
	X_5	4	5
	X_6	2.5	2
	X_7	15	12
	X_8	450	550
PC (day)	EVT—Initialisation	1	1
	EVT—Design	14	14
	EVT—Prototype	15	15
	EVT—EVT Testing	7	7
	DVT—T0 Mould	45	45
	DVT—EVT Testing	7	7
	DVT—T1 Mould	15	15
	DVT—DVT Testing	7	7
	PVT—T2 Mould	7	7
	PVT—Trial Production Run	25	25
	PVT—PVT Testing	10	10
	MP—Production Fine-tuning	7	7
	MP—MP Notice	3	3

Table 3. *Cont.*

Aspect	Parameters	HC2	New Case
HR (man-day)	RS—Hardware	21	21
	RS—Software	30	14
	RS—Structural Investigation	25	21
	RS—Product Testing	12	12
	RS—Research Coordinator	6	6
	PS—Product Management	12	12
	PS—Project Management	6	6
	PS—Trial Production Run	3	3
	PS—Product Testing	21	21
	SS—Art	3	3
	SS—Product Quality	3	3
Budget (CNY)	Design and Prototype	30,000	30,000
	Mould Development	300,000	250,000
	Trial Run	10,000	10,000
	Certificate Application	45,000	45,000

5. Results and Discussion

In this section, the performance of the proposed system from the domain experts' perspectives is analyzed, before and after system implementation. In addition, the managerial implications of the proposed system in the research and development (R&D) activities are outlined.

5.1. Empirical Evaluation of the System Performance

Although the cross-validation of different combinations of training and validation rates was conducted in the case study, the system performance in the case company was further validated. To effectively understand users' perspectives on the proposed system in the NPPM process, a survey before and after system implementation was undertaken by the NPD team, with a total of nine participating staff with extensive experience of NPD in case companies. The demographic details of the nine staff are summarized in Table 4. The interviewees in this empirical investigation were selected from two product streams in the case company.

Table 4. Demographic information of the interviewees.

Staff No.	Stream	Position	Years of Relevant Experience
1	A	General manager	21
2	A	R&D manager	8
3	A	Product manager	5
4	A	Product manager	6
5	A	Product manager	5
6	B	General manager	25
7	B	Product manager	19
8	B	R&D manager	23
9	B	Product manager	21

For the questionnaire, the measurement items are shown in Table 5, while the measurement scales followed the 5-point Likert scale. The entire survey was split into two sections—before and after the implementation of the proposed system—while corresponding briefing sessions were provided before answering the questionnaires. Regarding the second questionnaire, an in-depth briefing session was performed to educate the staff on CBR and transfer learning.

Table 5. Measurement items of the empirical investigation.

No.	Measurement Items
1	The current NPPM approach is good with respect to ease of implementation
2	The current NPPM approach is good with respect to ease of use.
3	The current NPPM approach is effectively compatible with other enterprise systems for the NPD process.
4	The security level of the current NPPM approach is satisfactory.
5	My overall performance for the current NPPM approach is positive.

As shown in Table 6, the results of the survey were summarized, while the Mann–Whitney U test was applied to evaluate the difference in the median before and after system implementation. Because the number of interviewees was limited to the case company, the use of the Mann–Whitney U test could effectively measure differences without checking for normality. Thus, it was suitable for the small-scale empirical investigations in the case study. Under the 95% confidence interval, it was found that the improvements in ease of use and system security were statistically significant following system implementation. When the 90% confidence interval was considered, the compatibility and overall performance were significantly enhanced. Consequently, the overall feedback from the interviewees was positive for system implementation in this case study, where the use of the proposed system effectively revamped the existing NPPM in the NPD process.

Table 6. Mann–Whitney U test for the statistical measurement.

No.	Average of the Scales		*p*-Value of the Mann–Whitney U Test
	Before	After	
1	3.111	3.667	0.105
2	3.111	3.889	0.021 *
3	2.556	3.556	0.068
4	3.111	4.000	0.048 *
5	3.556	4.222	0.076

Remark: The *p*-value with asterisk (*) denotes that the median differences of the measurement items are statistically significant at 95% confidence interval, and thus the median of the scale after the system implementation is significantly higher than the scale before the system implementation.

5.2. Comparison with the State-of-the-Art Approaches

In addition to the empirical evaluation to emphasize the practicality of the proposed system, a comparative evaluation with the state-of-the-art approaches was conducted to determine the academic value of this study. In order to formulate new-product portfolios, the conventional case-based reasoning mechanism was further revamped with a consideration of the customer preferences, in which the transfer learning for natural language processing was embedded to analyze customer comments available in the retail e-commerce platforms. Compared with existing work [14,19], the differences in terms of objectives, methodologies, and novel elements for the NPD decisions were summarized, as shown in Table 7. In the research methodology, the transfer learning for opinion mining was incorporated into the cycle of case-based reasoning so as to achieve the customer-centric NPD management, in which the continuous improvements and customer-centric thinking were orchestrated.

It was found that the concept of customer-centric thinking was included in NPPM through this study, while the transfer learning for BERT was designed and developed for the case-retrieval process. Unlike the theoretical development of the previous studies, this study provides a real-life case study in the printer manufacturing business to show the entire mechanism and process to effectively illustrate the value of the intelligent project portfolio management over a CBR cycle with opinion-mining capabilities. Regarding the technical aspects, the proposed work was developed not only for cost and profit optimization, but also for customer requirements and feedback on relevant products available in the market.

Table 7. A summary of state-of-the-art comparison.

	Work [14]	Work [19]	Proposed Work
Problem	• The simultaneous development of several products, long duration of product development, and usually limited amount of resources leads to difficulty to have effective management of NPD projects	The difficulties in choosing which products to develop, sell, maintain, and remove as the product portfolio in the candidate market	New-product portfolios are manually developed by experts, which lack the customer perspectives.
Objective(s)	• To formulate NPD projects with cost estimation	To maximize the project portfolio management value for existing and new products	To formulate customer-centric NPD projects with the aid of the INPPCS
Methodology	- CBR - Artificial neural networks	- Neural network - Mathematical programming	- CBR - Transfer learning for BERT
Novel elements for the NPD decisions	Cost estimation in the CBR cycle	An optimal balance of profit, budget, and risks constrained by the total budget and risk threshold	Customer opinion analysis in the CBR cycle
Result	More precise cost estimation obtained by ANN PA improves the selection of the most promising NPD portfolio and monitoring the performance of ongoing projects	Product portfolio must be replaced by the product/market portfolio if the overall profit is to be truly maximized.	Product portfolios are systematically formulated with analyzing customer requirements and expectations
Case example	No	No	A printer manufacturer

5.3. Managerial Implications

In the past, the new-product portfolio formulation and management fully relied on specific professionals who had extensive experience working on NPD [26]. Upper management only believed the decisions made by professionals, and thus the stage-gate model was applied to regularly monitor and adjust NPD projects so as to assign appropriate resources and talent. Such a human-driven approach involves a certain extent of bias and subjectivity, while professional knowledge cannot be effectively transferred to and inherited by other staff members [27]. Consequently, the quality and reliability of NPD projects were highly subjective for the experts and, therefore, the NPD process—in particular NPPM—was not sustainable for business development. With the aid of the proposed INPPCS, the overall procedures to manage product portfolios were standardized as the essential tool for NPD activities. New products, including improved products and brand-new products, could be developed according to the historical portfolios so as to allocate adequate budgets, resources, and talents. By doing so, the reliability and consistency of the entire NPD process could be improved, resulting in an increase in the likelihood of new-product success. In addition, based on historical practices, the NPPM process was almost entirely expert-driven, while customers had no stake in the project portfolio formulation. It was difficult to involve customers' perspectives in the traditional NPPM process, and thus customer requirements might not have been fully satisfied [28,29]. According to the mechanism of the proposed system, customer feedback on relevant products can be analyzed to understand up-to-date customer wants and needs in order to fine-tune the strategy for the setup of NPD projects. It is commonly understood that building a robust machine-learning model for NLP applications is relatively difficult, particularly in the collection of sample-rich datasets for model training. Therefore, the transfer-learning scheme proposed in this study is an effective approach in understanding customer feedback based on limited datasets, resulting in effective model training and validation [30]. The entire new-product portfolio configuration process can become dynamic and sensitive to customer feedback, so that a customer-driven NPPM can be built in the era of intelligent manufacturing. Under the paradigm of Industry 4.0, an increasing number of intelligent technologies and algorithms can be applied to revamp design, production, and logistics operations to improve productivity, service levels, and sustainability [31,32]. The power of machine learning should be leveraged to enhance the supply-chain capability in a dynamic and fluctuating business environment.

Furthermore, with the findings of the case study, the proposed system has a positive impact on NPD activities with regard to the design and development of new industrial printing equipment. Manufacturing companies involving NPD activities can, therefore, obtain similar benefits by using the proposed approach to standardize and automate new-product portfolio configuration and management. By referring to past successful NPD projects, future NPD projects can be formulated in a suitable manner to enhance the success of new products in the market.

5.4. Discussions on the INPPCS

With the aid of the proposed system in the NPD process, particularly the NPPM, its usefulness and feasibility have been verified through case studies on industrial printing equipment manufacturing companies. The case company specializes in offering industrial printing solutions, such as thermal printers for logistics operations and point-of-sales systems, which can be continuously evolved along with the recent technological advances, such as cloud computing and robotic process automation. Therefore, such a company is required to frequently launch NPD projects to revamp existing printing solutions and invent new equipment for industries. In order to manage a large set of NPD projects, an effective NPPM solution is needed to configurate the product portfolios and make go/kill decisions, balancing the resource allocation and commercial value of NPD projects.

In addition to verifying the feasibility and usefulness of the proposed system, a number of commercial values can be obtained, including customer satisfaction, return on investment, and market penetration. To assess the commercial value of these new products, a cross-sectional study, in which the proposed system and a traditional approach are implemented, can be conducted for a given period of time. Consequently, the impact of the proposed system can be quantified and benchmarked with existing approaches.

6. Conclusions

In summary, this study was motivated by existing challenges in the current manual NPPM process, which cannot satisfy the increasing customer and market requirements. Moreover, the reliability and consistency of NPPM are always questioned by the top management in manufacturing companies. Due to recent advances in artificial intelligence (AI), this study investigated the possibility of the integration of promising AI techniques to revamp the NPPM process, in which CBR was explored under the transfer-learning scheme for text classification. In the CBR mechanism, customer feedback is considered to enhance the case-retrieval process in order to avoid the dominance of product manufacturers in the NPD cycle. Therefore, a new-product portfolio can be built by referring to historical and successful cases, resulting in an enhanced quality of the new configurations. To verify the effectiveness of the proposed system, a case study in Gainscha (the case company) was conducted to revamp its NPD and NPPM processes in a systematic and standardized manner. Based on the empirical investigation of staff perspectives, it was found that the proposed system had a positive impact on NPPM, while relevant staff members were willing to work with the newly proposed system in order to build new project portfolios. In view of this research, this study contributes to both the academic and practical aspects of this topic. First, the main contribution of this study is its novel integration of CBR and transfer learning for text classification, which was proposed to determine attribute weights by considering customer reviews instead of mutual and intuitive approaches. Second, the entire NPPM process was standardized and computerized to achieve better portfolio quality and staff satisfaction.

Regarding the major limitations of this study, the proposed system was validated solely by a single manufacturer in China, while customer feedback was related to a specific group of products. Moreover, customers can be influenced by other existing customer reviews and, therefore, the interaction between customers should be considered for opinion mining. In future research, customer reviews of various products and customer interaction should be considered for opinion mining, while the proposed system can be further implemented in other manufacturing companies to generalize research findings on the improvements in customer satisfaction and portfolio quality. Furthermore, more case studies in different manufacturing processes, not only industrial printing equipment, can be considered to further evaluate the benefits obtained from the proposed system. The value of this research study in the manufacturing industry can, thereby, be generalized.

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