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The Perspective Classification of Balanced Scorecard with Ontology Technique

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ABSTRACT

The competition among Higher Education Institutions (HEIs), such as universities, worldwide is crucial. It is imperative for universities to maintain high-quality education and achieve and maintain their world ranking. Therefore, they must utilise performance management tools in their performance improvement efforts. The Balanced Scorecard (BSC) is a quality tool for performance management in universities that helps them to enhance, increase, and maintain their overall performance and ranking. When their strategy changes, the performance indicators must be revised and rearranged in accordance with the BSC form. The information needed for decision-making cannot be immediately available because there are delays in updating the performance management system. This creates a gap between performance improvement in HEIs and the BSC. To eliminate this gap, the question we need to answer is how to automatically upload the updated BSC perspectives into the performance management system to streamline the decision-making automatically. This paper aims to present the Perspective Classification of Balanced Scorecard with Ontology (PCBSC-Onto) framework for automatically classifying performance indicators into BSC's four perspectives using an ontological approach to support the dynamic capability of the management system's performance. The balanced scorecard ontology and performance indicator ontology created through this research were applied in the PCBSC-Onto framework. The experiment's results are based on the performance indicator data of a university in Thailand, and it presents how this framework and its algorithms contribute to increasing performance management ability in the HEI context. The accuracy rate of the PCBSC-Onto framework is 82.97% when compared to the accuracy of the modified Delphi method. The results reveal the accuracy of the proposed ontologies and algorithms on the data from the case study.

Keywords: Classification, ontology, balanced scorecard, performance management, case study.

INTRODUCTION

All countries recognise that universities are essential for developing the workforce to drive the economy (Kiriri, 2022). Higher Education Institutions (HEIs) worldwide focus on providing high-quality education, academic services, and research for their students and society. In addition, they attempt to maintain and improve their university's world rankings, such as their THE and QS rankings (Anuforo et al., 2019; Camilleri, 2021). The university ranking sites use performance indicators to assess and classify the HEIs quality to determine the university's ranking (Dill & Soo, 2005). The universities' ranking affects the universities' behaviour, culture, and policy. Therefore, the universities must review and revise their strategies, initiatives, and performance management to advance to a higher ranking level (Kohoutek et al., 2018; Wood & Salt, 2018).

The Balanced Scorecard (BSC) of Kaplan and Nortan (1996) links all performance indicators to one of four perspectives - financial, customer, internal business process, and learning and growth - which are consistent with the organisation's strategy. Moreover, BSC indicates implementation process guidelines to increase performance and promote continuous organisational improvement. The perspectives of the information generated by the BSC reveal the gaps in academic staff performance improvement. Moreover, BSC is an efficient tool for two-way communication among the academic staff and directors regarding governing the university's activities (Camilleri, 2021; Kaplan & Norton, 1996; Taylor & Baines, 2012). Implementing BSC in a university positively affects the university's staff, management, culture, and strategic communication. Furthermore, BSC enhances the overall performance, impacting the ability to improve the university's ranking (Anuforo et al., 2019).

The management of HEIs is an extremely complicated issue. The competition among HEIs, especially among traditional universities and e-universities (e.g., online), has dramatically affected educational managers' strategic decision-making (Berges et al., 2021; Chen et al., 2006; 2009; Storey, 2002). Performance indicators (PIs) are the indicators that can be used to track the team's performance and help the workflow of all the teams to align with the organisation's strategy. In such a cut-throat competitive environment, performance management systems must be able to timely process and present changes that affect the existing PIs that will have to be adjusted or deleted (Parmenter, 2020). Therefore, the management of PIs has become a powerful approach for promoting the university's performance improvement. Monitoring the appropriate PIs guarantees the chances of survival in this aggressively competitive arena (Anuforo et al., 2019). Many studies have examined knowledge-based systems employing ontology technology applications in the HEI context (Tapia-Leon et al., 2018). PIs and Balanced Scorecard ontology have been presented as the preferred concepts to improve performance management systems (del Mar Roldán-García et al., 2021; Navarro-Hernandez et al., 2006; Li et al., 2019).

As mentioned above, performance management based on the BSC concept is essential to improving the performance of HEIs and the universities' world rankings. Generally, universities must change their PIs when facing new competition, strategies, and challenges.

Then, as their PIs change, they have to rearrange them new PIs to fit the BSC perspectives. However, the improvement of the existing performance management system needs to be more practical regarding the automatic processing of the PI classifications into four domains in BSC. Hence, there is an exciting gap in these studies regarding how to automatically assign the HEIs new performance indicators to the proper BSC perspectives to ensure the performance management systems operate efficiently and on time. This research will create a system to automatically classify PIs into the BSC employing an ontology technique to ensure the capability of the performance management system to operate rapidly and efficiently in the HEI context.

The remainder of this paper briefly describes the conceptual background, the application of the BSC in HEIs, the use of ontology technology in organisations, and performance management at the Prince of Songkla University, Thailand. Then, we present the research framework and methodology. Finally, we explain the results and discuss the research's challenges.

RELATED WORKS

Application of the Balanced Scorecard in Higher Education Institutes

Kaplan and Norton (1996) created the BSC in 1990. The indicators of the BSC must point back to the organisation's strategy from four perspectives: financial, customer, internal business process, and learning and growth. BSC is an operational measurement, a tool for a strategic management system (Guenther & Heinicke, 2019; Kaplan, 2012). When using the BSC as a strategic management tool, each BSC perspective will determine the organisation's objectives, measures, targets, and initiatives. From the financial perspective, this view has two main measurement directions. The first is strategic themes, such as revenue growth and mix, cost reduction or productivity improvement, and asset utilisation. The second is the business unit strategy related to growth, sustainability, and harvest. The core measurement factors' customer-related aspects consist of market share, customer retention, customer acquisition, customer satisfaction, and customer profitability. When a customer is satisfied, it positively affects the level of customer retention, customer acquisition, and customer profitability. Conversely, customer retention and customer acquisition affect customer profitability and market share.

From the internal business process perspective, BSC considers three processes within the generic value chain model: innovation processes, operations processes, and post-sale service processes. This perspective focuses on efficient operation and cost reduction in the organisation. Finally, from the learning and growth perspective, the core measurements include four factors: performance results, employee retention, employee productivity, and employee satisfaction. When an employee is highly satisfied, this positively affects employee retention and productivity. In addition, employee retention and employee productivity affect the end results. The enablers or motivators of employee satisfaction are staff competency, technology infrastructure, and climate for action. Moreover, this perspective also considers the aspects related to employee motivation, empowerment, and alignment (Kaplan & Norton, 1996).

Many universities have employed BSC to enhance the university's ranking and improve university management by adapting its concepts and methods to traditional processes and performance monitoring associated with the BSC indicators (Alani et al., 2018; Anuforo et al., 2019; Kiriri, 2022; Nurcahyo et al., 2018; Valdez et al., 2017). Alani et al. (2018) reported that the four domains of BSC were associated with a university's performance in Oman. As a result, the key performance indicators incorporated in the BSC became an excellent strategic tool to monitor and evaluate the university's achievement. Moreover, they clarified that most staff knew and understood their department's and university's strategies. However, less than half of the staff knew the concepts of BSC. In the same year, Nurcahyo et al. (2018) applied the BSC to determine the strategy of the engineering faculty at the University of Indonesia. The analytical hierarchy process was used to map the strategic theme and prioritise the strategies based on the vision and mission of the faculty. The Borda and triangulation methods were used in the strategy selection process to select the strategies that were in line with the university's strategic plan. Then, the indicators for chosen strategies were arranged according to BSC's four perspectives.

Meanwhile, Anuforo et al. (2019) studied BSC implementation at a university in Malaysia. They found that applying the BSC philosophy, along with the willingness to support and participate among staff, the top executive commitment, internal culture, and communication strategy, was significantly related to the university's performance and rankings. In addition, Valdez et al. (2017) applied the four perspectives of BSC to business intelligence tools for monitoring the strategies within a university. First, they focused on the financial perspective: income, funds, and asset management. Second, they examined the students' perspective to see the customers' perspective. Third, from the internal perspective, they explored value chain improvement. Fourth, they examined the university's human capital improvement and internal information to look at the learning and growth perspective. Finally, regarding business intelligence, they observed how BSC supported the processes of management and decision-making within the university context.

De Jesus Alvares Mendes Junior and Alves (2023) analysed the 578 articles from the Web of Science and Scopus between 2002 to 2022 and categorised the BSC application in the education sector to be 4 clusters: (1) the diversity of the BSC; (2) strategic management with the BSC; (3) statistical methods to manage the BSC, and (4) the BSC strategy map. The study of De Jesus Alvares Mendes Junior and Alves (2023) showed that most of the education about BSC in HEIs has focused on performance improvement and strategic management. From the literature review, it is clear that the BSC is a key method for enhancing university rankings and the efficiency of the performance management system (Alani et al., 2018; Anuforo et al., 2019; Nurcahyo et al., 2018; De Jesus Alvares Mendes Junior & Alves., 2023). However, a significant gap exists in understanding how to automatically modify the performance management with BSC when the performance indicators change. In response to this, our research proposes a novel approach. We aim to extract the relationship between BSC factors and create a BSC taxonomic model using ontology. This unique BSC ontology will automatically classify the PIs into the appropriate BSC perspective, a method that has not been explored before.

Using Ontology Technology in Organisations

Ontology is a representative knowledge model that is depicted by a set of classes, properties, and the relationships between the classes (Gruber, 2009). The advantage of ontology in a data-driven organisation is the ability to map the data, which allows the user to discover the relevant data sources (Tapia-Leon et al., 2018). Therefore, the application of ontology is pervasive in organisations such as healthcare, business, industry, and HEIs. Mostly, they adapt and modify the ontology to implement their knowledge-based systems (Bai et al., 2014; Chen et al., 2019; Walzel et al., 2019; Zeebaree et al., 2019). Applying ontology technology in HEIs has been studied from many perspectives, such as curriculum design, e-learning, academic recommendation, academic information retrieval, and evaluation. For example, the ontology concept can be applied to mapping the course and resources for curriculum development and sharing the curriculum's content in another educational context. In an e-learning system, ontology has been used to build a personalised e-learning system to support students. Furthermore, by employing ontology techniques for knowledge management, the HEIs improved the recommendation system and information retrieval to suggest suitable courses, books, subjects, and other things related to the universities. Furthermore, the ontology was implemented to avoid interoperability problems in academic evaluations by integrating the relevant data from multiple systems (Tapia-Leon et al., 2018).

Many researchers have presented the existing ontologies in HEIs with their taxonomy. For example, Zemmouchi-Ghomari and Ghomari (2013) created an ontology-based reference of publications in the university domain. They indicated the relations between three classes: role, location, and research work. They included three subclasses of the type of role: student, faculty, and governing board, and two subclasses of faculty: department and faculty member. The faculty classification included administrative and academic staff as its subclasses, with the researcher being a subclass of academic staff and the teacher being a subclass of the researcher. Moreover, the publication classification was a subclass of class research work. These classes created many relationships, such as "appointed_to, belongs_to, composed_of, cooperates_with, enrolled_by, studies_at, and supervised_by." In another research study, Zeebaree et al. (2019) built an ontological model to rectify problems related to the relations between user requirements and the content in an e-learning system. There were three main classes: college, people, and institute. The relationships between this ontology consisted of "administrator, has, researcher, school_has_element, course_must_have, has_course, studies, and teaches."

For performance indicator ontology in an organisation, del Mar Roldán-García et al. (2021) explained the key performance indicator (KPI) ontology using four main classes: goal, indicator, relationship, and aim. Furthermore, the indicator classification had three subclasses: measure, KPI, and key result indicator (KRI). The relationship class had two subclasses: contribution and decomposition. The relationships between these classes were "has_individual, has_subclass, has_relationship, inconsistent, indicator_direct, indicator_reverse, monitors, redundant, with goal, goal_direct, goal_reverse." Meanwhile, Li et al. (2019) proposed a KPI ontology to focus on the semantic calculation process. Their model depicted the relationships between class stakeholders, performance goal, KPI, KPI calculation, KPI evaluated object, interval KPI value, mathematical model, and equation. The subclasses of KPI were "strategic_KPI, tactical_KPI, and operational_KPI" and "assumption, universal_constant, and variable" were the subclasses of the mathematical model. The relationship examples in this ontological KPI model included "has_performance_goal, has_associated_KPI, has_calculation, contains_variable."

Navarro-Hernandez et al. (2006) presented an ontology model for BSC. They illustrated BSC ontology in four main classes: objective, initiative, perspective, and measure. There were four objectives from the BSC perspective: customer objective, financial objective, business process objective, and learning and growth objective, which were the subclasses of objective. In the same way, BSC's four perspectives were the subclasses of perspective. The object property between all classes was only "is_a." The literature review about using ontology technology in organisations revealed that ontology approaches have been applied in various aspects of the HEI context, especially performance management (Tapia-Leon et al., 2018). Many works apply the ontology in the KPI domain for performance system improvement (Li et al., 2019; Zeebaree et al., 2019; del Mar Roldán-García et al., 2021). The existing BSC ontology presents general relationships unsuitable for automatically classifying the KPIs into the four views of BSC; this is the study gap, a crucial area that needs to be addressed. Therefore, this research will modify the existing ontologies to create a new ontology for BSC and performance indicators to apply in this research framework.

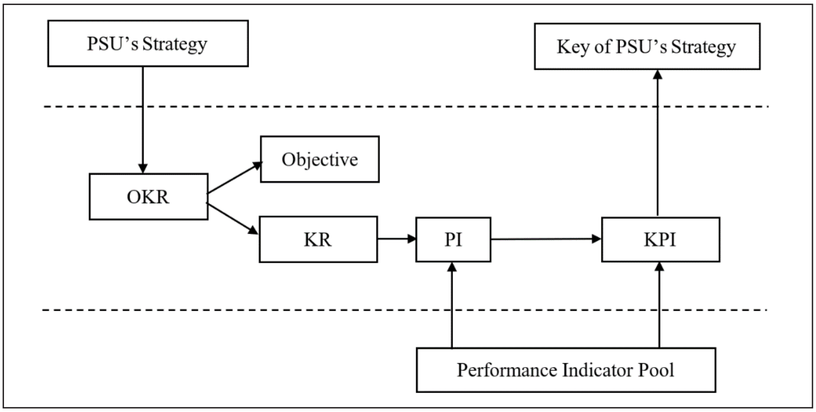
The Performance Management System of the Prince of Songkla University

Prince of Songkla University (PSU) is recognised as the best-quality university in the southern region of Thailand by QS World University Rankings for the year 2021 (Quacquarelli Symonds, 2021). This university has five campuses in Songkhla, Pattani, Phuket, Surat Thani, and Trang. PSU has 13 KPIs and 5 Objectives and Key Results (OKRs). The OKRs consist of 47 Key Results (KRs) that are performance assessment indicators according to the strategic plan (Department of Policy Strategy and Planning, 2018). PSU consists of 39 faculties, 340 curriculums, and 33,573 students pursuing undergrad, graduate, and doctoral degrees on 5 campuses (Department of Policy Strategy and Planning, 2021).

From interviews with some of the staff members of the Planning Division who are involved in the performance management process, it was found that the Planning Division is the central agency in managing KPIs and OKRs by using the reporting indicators. All relevant agencies are responsible for submitting information upon request from the Planning Division. Figure 1 shows how the Planning Division uses OKRs to drive the strategies of PSU by dividing the OKRs into five areas: world-class university, the core of human resource development at all ages/levels, academic service projects that strengthen sustainable economic, social, health, natural resources and environment, PSU one system, stability, and financial constancy, that correspond to the missions in each area of the university. Each OKR has two essential characteristics: (1) goals (objectives), where the objectives are separated into 2-5 KRs, and (2) measure factors and effects (KRs), where each KR is selected from a pool of performance indicators (PIs). More than 300 indices have been used in the past or were newly created. Therefore, each KR consists of a group of 2-5 PIs.

Figure 1

Relationships between the KPIs and OKRs of PSU



When considering the relationships between the OKRs and KPIs, it was found that the university currently focuses on reporting annual results and monitoring results through OKRs. Therefore, the OKRs correlate with the KPIs when a PI is an index essential to measuring the achievement of the university's strategic plan. This PI would then be classified as a vital PI. Then, they are called KPIs, which reflect the overall picture of management. KPIs are selected from the indicator warehouse or are the same as the PIs defined in the KR. Figures 2 and 3 describe the data collection process; at the beginning of this process, the Planning Division analyses and classifies the data to support the calculation of indicators. Then, whether the data exists in the information system or not, the Planning Division will analyse it by exploring the relationships between the columns in the database systems or by asking the owner of the information system.

Figure 2

Permission to Access Information

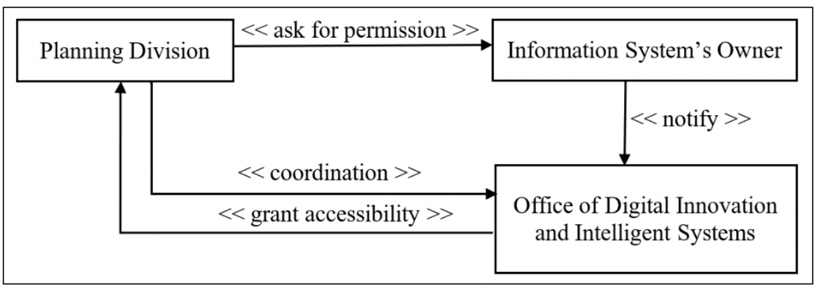
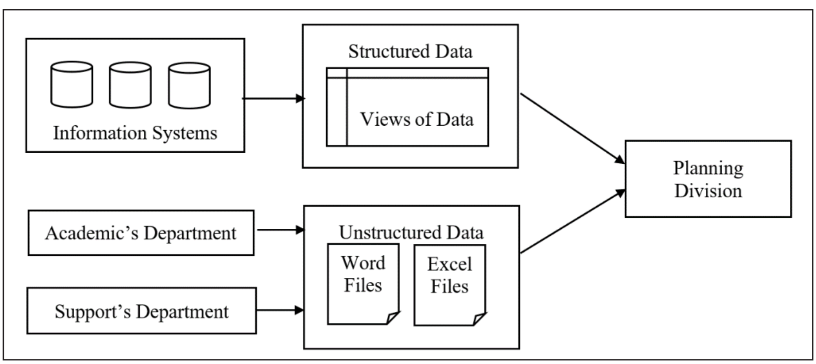


Figure 3

The Process of Collecting Data on KPIs And OKRs From the 5 Campuses



The survey results from the Planning Division were obtained in two ways: First, if the data already exists in the information system, the Planning Division must obtain permission from the owner of the information system to access such information. When allowed, the Office of Digital Innovation and Intelligent Systems (the information security agency) will create the views of the data as requested by the division and determine the access rights to the views. The information system owner may not grant the right to request information. However, in that case, the owner of the information system will summarise the data and send it as a document file. Second, if there is no information in the system, the Planning Division will request the faculties and relevant agencies. For example, the Division of Student Development and Alumni Relations and the Office of Education and Learning Innovation in order for these agencies to deliver information that is not available in the information system but related to the reporting of various indicators, by sending it in as a document file.

When the Planning Division has gathered all the information, it will calculate the indicator index specified in the OKRs and categorise data to generate the representation. Then, the planning division will summarise the results by calculating various index values. After that, the results will be presented as a dashboard using Google Data Studio or Excel. The data presentation appears as a calculated summary of KPIs or OKRs and uses pie charts and bar charts to compare the data. The nature of the representation is in the form of descriptive analytics, which only presents the overall number of the results.

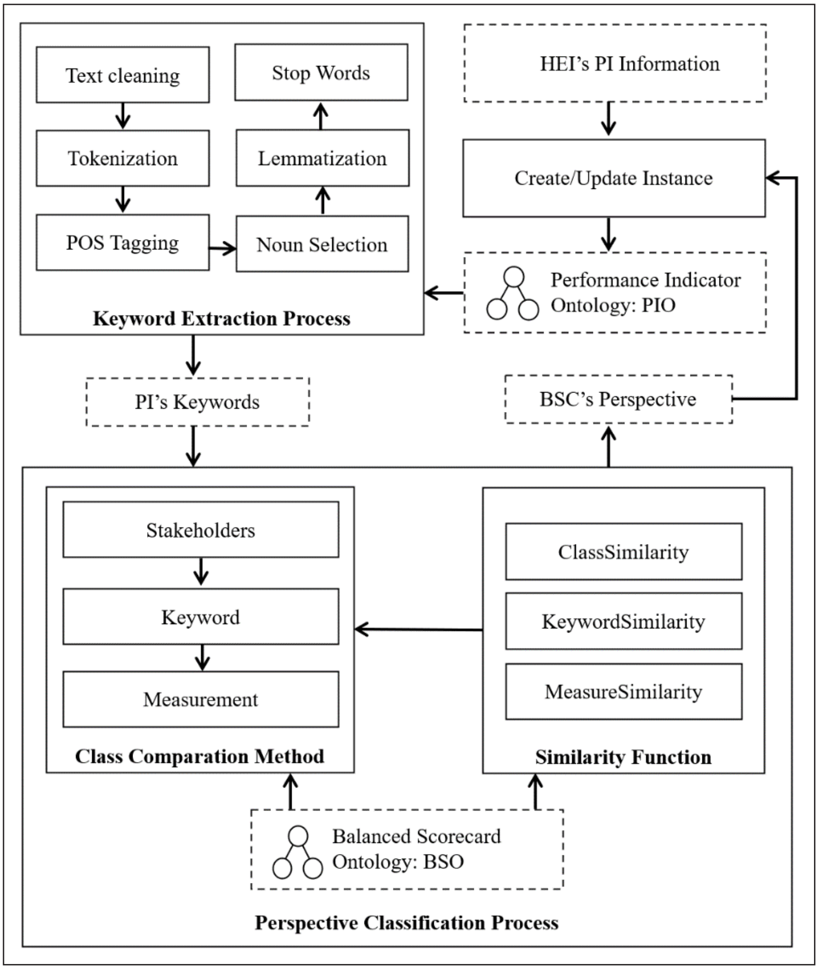
METHODOLOGY

Research Framework

The Perspective Classification of Balanced Scorecard with Ontology Technique (PCBSC-Onto) Framework based on HEIs context is illustrated in Figure 4. The popular algorithm for classifying classes based on textual data is the Multi-Class Multi-Level (MCML) algorithm (Musa et al., 2024). However, the MCML algorithm is unsuitable for this research because the study's approach follows the unsupervised learning method. We create a new algorithm and process that is applied to the research framework.

Figure 4

The PCBSC-Onto Framework



This framework has two main processes: (1) the keyword extraction process and (2) the perspective classification process. Before starting these processes, the user must input the HEIs PI information to create the instances following the Performance Indicator Ontology (PIO). Then, the PIO is used as the input for the keyword extraction process. This process reads the names of all the instances in the PI classes in the PIO. Then it performs the extraction process to find the important keywords in the PI's name. The keyword extraction process includes six methods: text cleaning, tokenisation, parts of speech (POS) tagging, noun selection, lemmatisation, and stop words. This process determines PI's keywords that move to the next process, the perspective classification process, which reads the class properties and relationships from the Balanced Scorecard Ontology (BSO) and uses the similarity function ClassSimilarity, KeywordSimilarity, and MeasureSimilarity as part of the algorithms for classification.

After that, the perspective classification process uses the PI's keywords to perform the next three steps using the class comparison method to compare the keywords with stakeholders, keywords, and measurement. First, the comparison method must read the information from the BSO and apply the similarity function to indicate the proper BSC perspective for each PI. Then, multiple algorithms are created to process all the data to generate the BSC's perspective results. The descriptions of these algorithms are explained in the next section. Finally, the final result of the perspective classification process is sent back to update the instances in the PIO.

Research Methodology

The following research methodology was utilised.

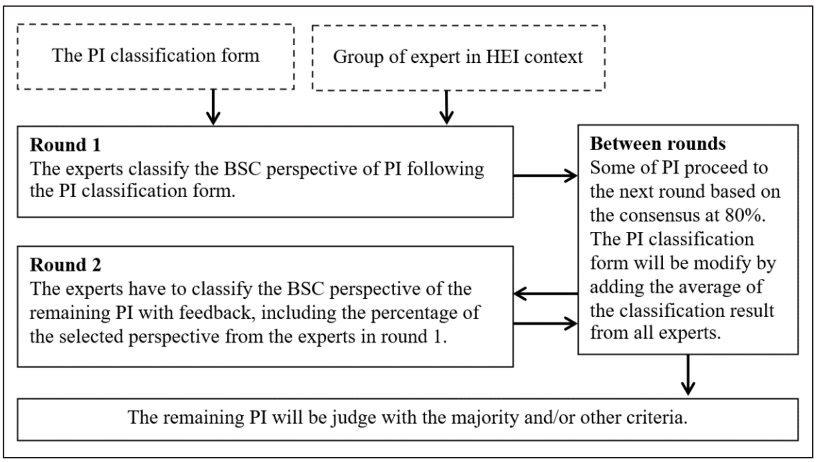
1. A structured literature review of the existing literature was performed to find the concepts related to classifying performance indicators into BSC's four perspectives automatically in the HEI context. Then, once we understood the relevant approaches, we adapted the appropriate theories to our framework.
2. The Performance Indicator Ontology (PIO) promoted by del Mar Roldán-García et al. (2021) and Li et al. (2019) was modified and adapted to the HEI context along with the relationship analysis of factors in the PSU's strategic plan for 2018-2022 (Department of Policy, Strategy and Planning, 2018).
3. The Balanced Scorecard Ontology (BSO) was created by analysing the relationships between the BSC's four perspectives and measurements based on the book by Kaplan & Norton (1996) and using the existing BSC ontology of Navarro-Hernandez et al. (2006) as the guideline. The classes used for the BSO were selected from Camilleri (2021), Kiriri (2022), and Valdez et al. (2017).
4. The PCBSC-Onto framework was tested using the PSU PI information. The accuracy rate of the algorithm in the PCBSC-Onto framework was calculated by comparing expert judgment

and the framework. The Delphi technique from Barry et al. (2016) and Drumm et al. (2022) was applied to determine the answer from expert judgment. The adapted Delphi method is depicted in Figure 5. This method set the minimum threshold for consensus at 80% of the experts selecting the same perspective in rounds 1 and 2. The remaining PIs that did not reach the threshold for consensus in round 2 will use the majority view or other criteria to judge the perspective.

5. Summarisation and discussion of the experiment's results.

Figure 5

The Adapted Delphi Method for Perspective Classification by Experts



RESULTS AND DISCUSSION

The Performance Indicator Ontology (PIO)

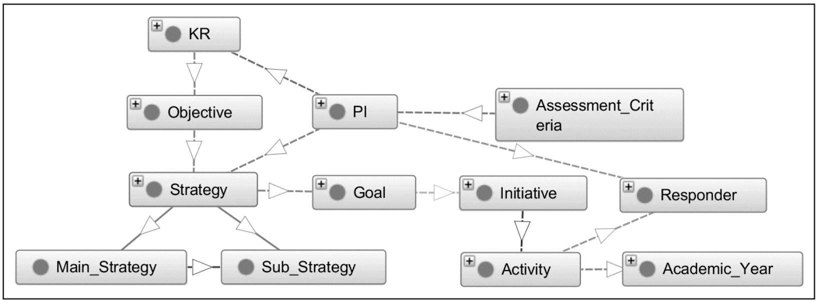
The PSU strategic plan for 2018 - 2022 and the existing KPI ontologies were analysed and synthesised to create the PIO for the HEI context. Figure 6 shows the relationships between the 12 classes in the PIO: strategy, main_strategy, sub_strategy, goal, initiative, activity, academic_year, responder, objective, KR (key and result), PI (performance indicator), and assessment_criteria.

The PI classifications consist of seven data properties: definition (type: string), formula (type: string), level of measurement (type:

string), KPI (type: boolean), OKR (type: boolean), BSC perspective (type: string), and status (type: string). The goal classifications consist of two data properties: change (type: string) and ultimate goal (type: boolean). Finally, assessment criteria classifications consist of two data properties: criteria (type: string) and year (type: string).

Figure 6

Performance Indicator Ontology (PIO)



PIO presents the path of consistency between class strategy and the other classes. All classes in the PIO have a relationship together. The names of all the relationships are presented in Table 1. The strategy classification has two subclasses: main_strategy and sub_strategy, and only the main_strategy class has sub-strategies. Every strategy has goals, each goal has initiatives, and an initiative has activities, and all activities must set the academic year and the responder into action. The class responder is the person or department that manages the PIs. There are two views of performance measurement: (1) the KPI view, where PI class acts as the KPI of class strategy and class assessment criteria are the PI's criteria, and (2) the OKR view, where the PI class is the indicator of KR class. Therefore, KR class is the key and result of the objective classification, and the objective classification must correspond to the strategy class.

Table 1

The Relationships Between All of the Classes in the PIO

Domain	Range	Object Property
Initiative	Activity	has_activity
Strategy	Goal	has_goal

(continued)

Domain	Range	Object Property
Goal	Initiative	has_initiative
Activity, PI	Responder	has_responder
Main Strategy	Sub Strategy	has_sub_strategy
Assessment Criteria	PI	is_criteria_of
PI	Strategy	is_kpi_of
KR	Objective	is_kr_of
PI	KR	is_pi_of
Objective	Strategy	correspond_to
Activity	Academic Year	set_schedule

The instance in the PIO will be created by a user who inputs the HEIs PI information into the electronic form based on the HyperText Markup Language (HTML). This form must be designed based on the properties of the PIs of the HEI. We focused this study on the method for classifying PIs into the four perspectives of BSC. Next, we created the names for the 47 instances used to classify the PIs. An example of a PI from the PSU case study is illustrated in Table 2.

Table 2

An Example of PSU's Performance Indicators

Name of PIs
Number of international publications
Amount of external research funding
Percentage of the teacher who passed the instructor competency assessment from level 2
Number of patented innovations/petty patents
Percentage of courses accepting students as planned per total number of courses
Number of branches ranked in QS Ranking
Employment percentage of graduates
Average monthly income of graduates
Number of courses for upskill, reskill as non-degree programs that can be used to accumulate credits
Number of courses with online teaching style, MOOC
Number of short-term training courses
Number of activities/volunteering projects for the benefit of the mankind

(continued)

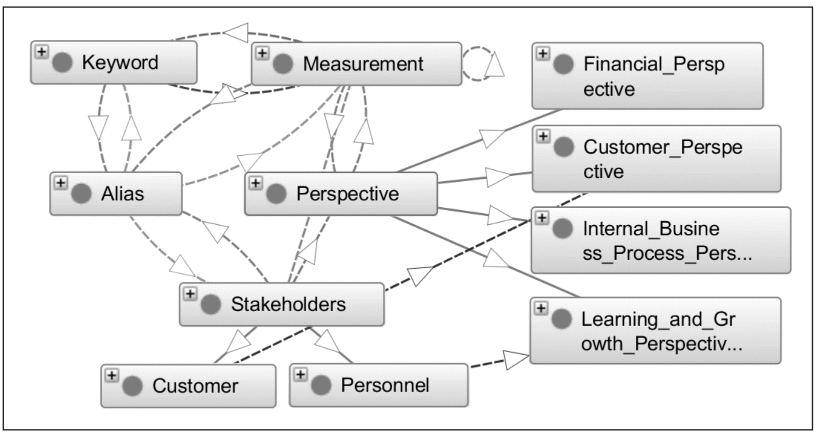
Name of PIs
ranking of universities according to SDG ranking criteria
Number of faculty who passed EdPEx 200
Percentage of income from various forms of education management
Percentage of increased research income

The Balanced Scorecard Ontology (BSO)

The main concepts of the Balanced Scorecard from Kaplan and Norton (1996) and the existing BSC ontologies were utilised to create the BSO that is represented by the model in Figure 7. There are five main classes; perspective, stakeholders, measurement, keyword, and alias. The perspective class has four views of BSC as its subclasses, and the stakeholder class has customer and personnel as its subclasses. Every subclass in the perspective class has some words to represent the measurement factor. Moreover, every word has an inverse relation with the class's measurement. The stakeholders class can be related to both the measurement and to a BSC perspective; for example, the personnel class can refer to the learning and growth perspective.

Figure 7

Balanced Scorecard Ontology (BSO)



The class measurement has a self-relation, so some factors impact other factors, such as customer satisfaction classification, which impacts customer retention classification. The class keyword collects the measurement factor keywords extracted from the literature review. Furthermore, this class has direct and inverse relationships for the reference with the class measurement. Class alias consists of synonyms and pseudonyms for the class keywords, measurements, and stakeholders. Furthermore, a class alias can refer to a class and also be referred to by a class. The names of all the relationships mentioned above are shown in Table 3.

Table 3

The Relationships Between All of the BSO Classifications

Domain	Range	Object Property	Inverse Relationship
Stakeholders, Keyword, Measurement	Alias	has_alias	is_alias_of
Alias	Stakeholders, Keyword, Measurement	is_alias_of	has_alias
Measurement	Keyword	has_keyword	is_ keyword_of
Keyword	Measurement	is_ keyword_of	has_keyword
Perspective	Measurement	has_measure	is_ measure_of
Measurement	Perspective	is_ measure_of	has_measure
Measurement	Measurement	impact_to	-
Stakeholders	Perspective	is_view_of	-
Stakeholders	Measurement	related_to	-

An example of a word list or member of the classes and subclasses in the HEI context is displayed in Table 4. Every word in each class is the instance that binds the relationships between classes to the BSO and represents the knowledge to use in classification processing.

Table 4

The Example of a Word List in of the BSO Classifications

Class Name	Word List
customer	alumni, graduate, student, parents, government, industry, social, business, and employer
personnel	academic personnel, support personnel

(continued)

Class Name	Word List
measurement	acquisition, alignment, business unit strategy, capability, empowerment, improvement, innovation, motivation, productivity, profitability, reduction, results, retention, satisfaction, strategic financial themes
keyword	accuracy, capital, citation, clarity, cost, culture, cycle time, energy, expense, growth, human, impact, infrastructure, investment, new, payback, payment, product, publication, quality, ranking, return, revenue, sales, saving, size, speed, team, technology, training, unprofitable, visit, warranty
alias	course, curriculum, education, knowledge, major, research, paper, teacher, instructor, lecturer, professor, learner, staff, mankind, public, environment, facility, income, funding

The PCBSC-Onto Framework Processing and Evaluation

After that, we add PIO to the keyword extraction process and BSO to the perspective classification process in the PCBSC-Onto framework. The keyword extraction process is described in Algorithm 1. The keyword extraction process starts with loading the PIO and BSO, and then reading all names of the members in the PI class. The name of each PI is in text form. Next, the text is cleaned by removing numbers and special characters. The cleaned text is then tokenised by breaking the text into words and, then, every word will be bound by their parts of speech (POS) in tuple form (word, tag). Finally, we build the noun selection method based on the priority order of nouns in the sentence. A noun that acts as an adjective is not the main noun, and a noun behind the preposition "of" is more important than one in a primary position.

Hence, the noun selection method selects only the main nouns from the list of tagged words. Next, the main nouns are lemmatised into a standard form. Then, the nouns that do not present a valuable meaning in the text are removed. Finally, all nouns that pass all processes become the keywords for the PIs sent to the prospective classification method. The methods of processes are as follows: text cleaning, tokenisation, POS tagging, lemmatisation, and stop words from the natural language toolkit (NLTK) in the library of Python are applied.

Algorithm 1: Keyword Extraction

```
Data: performance indicator ontology: PIO,
      balanced scorecard ontology: BSO
Load PIO, BSO
PI = []
Foreach pi in PIO.PI.subclasses() do
|   PI.append(pi.name)
end
Foreach i in len(PI) do
|   keywords = [], noun_order = 0, word_type = ["n"]
|   pi = Tokenization(Cleaning(PI(i)))
|   pos_tagged = POS_tagging(pi)
|   Foreach word, pos in pos_tagged do
|   |   if word = "of" then
|   |       keywords = keywords [ : -1]
|   |   if pos in word_type then
|   |       noun_order++
|   |       if noun_order is not 1 then
|   |           keywords = keywords [ : -1]
|   |           words = Stopwords(Lemmatization(word, pos=pos))
|   |           keywords.append(words)
|   |       else
|   |           words = Stopwords(Lemmatization(word, pos=pos))
|   |           keywords.append(words)
|   |   else
|   |       noun_order = 0
|   end
|   CheckPerspective(keywords)
|   update PIO
end
```

The perspective classification process is described in Algorithm 2. This process begins with every keyword from the keyword extraction process being subjected to three steps of class comparison: stakeholders, keywords, and measurements.

Algorithm 2: Perspective Classification

```
Function CheckPerspective(keywords)
    Foreach k in keywords do
        Foreach sh in BSO.Stakeholders.subclasses() do
            cs = ClassSimilarity(sh.name, k)
            if cs is true then return sh.is_view_of
            alias = list(sh.inverse_restrictions(BSO.is_alias_of))
            as = ClassSimilarity(alias, k)
            if as is true then return sh.is_view_of
            Foreach sc in sh.subclasses() do
                scs = ClassSimilarity (sc.name, k)
                if scs is true then return sh.is_view_of
                alias = list(sc.inverse_restrictions(BSO.is_alias_of))
                as = ClassSimilarity(alias, k)
                if as is true then return sh.is_view_of
            end
        end
        Foreach ks in BSO.Keyword.subclasses() do
            cs = ClassSimilarity(ks.name, k)
            if cs is true then KeywordSimilarity (k)
            alias = list(ks.inverse_restrictions(BSO.is_alias_of))
            as = ClassSimilarity(alias, k)
            if as is true then KeywordSimilarity (k)
        end
        Foreach m in BSO.Measurement.subclasses() do
            cs = ClassSimilarity(m.name, k)
            if cs is true then MeasureSimilarity(k)
            alias = list(m.inverse_restrictions(BSO.is_alias_of))
            as = ClassSimilarity(alias, k)
            if as is true then MeasureSimilarity(k)
        end
        return "Internal Business Process Perspective"
    end
return
```

The perspective classification process can stop before all three steps are completed if this process meets the BSC perspective and returns a result. Step 1, check the similarity between a keyword and all instances of the class stakeholders with the ClassSimilarity function. If the similarity is true, return to the BSC perspective referred from class stakeholders. Next, select all alias classes to compare the class stakeholders using the inverse relationship of class. Then, check the similarity between the class alias and the keyword using the ClassSimilarity function. Finally, this step will repeat the method with all subclasses of the stakeholders class.

The ClassSimilarity function in Algorithm 3 is a similarity comparison between the keywords and related classes in the BSO. This function checks the similarity with the "fuzz.token_set_ratio" library. If the accuracy rate is more than or equal to 80 percent, then the keyword and the class name are similar.

Algorithm 3: ClassSimilarity Function

```
Function ClassSimilarity (class, keyword)
    accuracy = fuzz.token_set_ratio(class, keyword)
    if accuracy >= 80 then return true
return
```

Step 2: check the similarity between a keyword and all members in the keyword class with the ClassSimilarity function. If the similarity is true, the KeywordSimilarity function will be used to find the proper BSC perspective. Next, all the alias classes of the selected keywords are compared by using the inverse relationship of the class keyword, then the process for Step 2 runs in a continuous loop until the last keyword is classified. Step 3: check the similarity between the keyword and all members in the measurement class using the ClassSimilarity function. If the similarity is true, the MeasureSimilarity function will be used to find the proper BSC perspective. The following method will select all instances of the class alias to compare with all instances of the class measurement using their inverse relationship, and then Step 3 runs in a continuous loop until the last keyword is processed. Finally, in cases where there is no similarity match, the perspective classification process will return to the internal business process perspective.

The KeywordSimilarity and MeasureSimilarity functions in Algorithms 4 and 5 are a little different. They are the methods for searching the class related to the keyword using an inverse relationship. The result of the class is a list that has to checked to determine "Is the financial perspective in the list?" with the "difflib.get_close_matches" library. If the answer is yes, then that result is returned to the BSC's perspective as a financial perspective, but if the answer is no, then it will return the name of the perspective class. Only the KeywordSimilarity function must be used to create a list of referred classes because a keyword can refer to many measurements. After that, they are looped to read all members in the list using the same method as the MeasureSimilarity function.

Algorithm 4: KeywordSimilarity Function

```
Function KeywordSimilarity (keyword)
    K = BSO.is_keyword_of
    m=[]
    Foreach k in K do
    |   m = m + list(k.inverse_restrictions(BSO.has_measure))
    end
    if difflib.get_close_matches("Financial Perspective", m) is true then
        return "Financial Perspective"
    else
        return m
return
```

Algorithm 5: MeasureSimilarity Function

```
Function MeasureSimilarity (keyword)
    m = list(keyword.inverse_restrictions(BSO.has_measure))
    if difflib.get_close_matches("Financial Perspective", m) is true then
        return "Financial Perspective"
    else
        return m
return
```

After the algorithms of the PCBSC-Onto framework were created, we classified the PIs into BSC's four perspectives using the Delphi technique. The results from five examining experts are summarised in Table 5. The round 1 results had 18 PIs that reached the 80 percent consensus level. Round 2 was separated into two methods of reaching consensus: (1) 20 additional PIs reached the 80 percent consensus level among the experts, and (2) there were nine PIs that the majority (3 out of the 5 experts) agreed on and were considered to have reached consensus as a result.

Table 5

The Number of PIs in the Consensus Agreement

Round 1	Round 2		Total
at 80% of consensus	at 80% of consensus	by majority	
18	20	9	47

Table 6

The Accuracy Rate of PCBSC-Onto Framework

Judge	Number of PI in each BSC's Perspective			
	Customer	Financial	Internal Business Process	Learning and Growth
Experts	18	6	15	8
PCBSC-Onto Framework	13	6	13	7

Remark: Accuracy rate in overall = 82.97%

Table 7

The Results of the Mismatches Between the Experts and the Framework

No.	PI	Result Consideration	
		Experts	PCBSC-Onto Framework
1	Number of academic works for commercial use	C	IBP
2	Number of patented innovations/petty patents	C	IBP
3	Percentage of courses accepting students as planned per total number of courses	C	IBP
4	Good performance (O-NET score)	C	LG
5	Number of times that professors are invited as speakers/specialists to provide academic services to both internal and external agencies	C	LG
6	Number of foreign teachers working full-time	IBP	LG
7	Number of selected students participate in the international cultural exchange program	IBP	C
8	Number of work/innovation of students who received national/international awards	LG	C

Remark: C = Customer, F = Financial, IBP = Internal Business Process, LG = Learning and Growth

The result of PI classification from experts was used as the input for calculating the accuracy rate of all the algorithms in the PCBSC-Onto framework. Table 6 shows the PIs matching the experts and the PCBSC-Onto framework. The accuracy rate of the algorithm in the PCBSC-Onto framework was 82.97 percent, and Table 7 presents the details of the mismatch results. The most mismatched result appears from the customer's perspective. The mismatched results happened due to the differences in interpretations between the experts and the PCBSC-Onto framework.

This study created the PCBSC-Onto framework as the solution for automatically classifying the performance indicators from the perspective of the Balanced Scorecard. The results present (1) the structure and relationships between all classes of PIO and BSO, (2) the algorithm for the automatic classification of the KPIs into BSC four perspectives, and (3) the algorithm's accuracy evaluation using the Delphi technique. The accuracy of all the models and algorithms of the PCBSC-Onto framework, based on testing on a case study, was 82.97 percent.

CONCLUSION

The crucial effects of competition in the HEI domain means their performance management systems have to be up to date use performance indicators which follow the BSC concept. When their performance management systems are more intelligent, they will create greater chances of survival in the competition. This paper attempts to shed light on presenting the automatic classification of new performance indicators into BSC perspectives for operating performance management systems in a timely, efficient manner. The proposed PCBSC-Onto framework and all the processes and results are presented. This includes the Performance Indicator Ontology (PIO), the Balanced Scorecard Ontology (BSO), the keyword extraction algorithm, the perspective classification algorithm, the ClassSimilarity function, the KeywordSimilarity function, and the MeasureSimilarity Function. Based on the experiment's results, the accuracy rate of this framework is 82.97% compared with the experts' consensus opinions based on the performance indicators of the PSU, Thailand. The accuracy score indicates that the PCBSC-Onto framework's processes can be applied to automatically classify performance indicators into

Balanced Scorecard perspectives to increase the rapid classification capability of performance management systems in the HEI context. The PCBSC-Onto framework offers a practical means for HEIs to begin their journey toward implementing the Balanced Scorecard into their performance management systems. In future work, the PCBSC-Onto framework will be integrated into the business intelligence system as part of the system for data visualisation in the strategic decision support systems of HEIs.

The study acknowledged the following limitations of the results. First, this research tests the accuracy of the invented BSC ontology using only one case study, which does not refer to the suitability of using this ontology in another university. Future research will develop the BSC ontology in a general form that can apply to various universities. Second, this study's result analysis does not go deep into sensitivity analysis to gain insight into the proposed solution's reliability and robustness. Future work will analyse the results with sensitivity analysis to answer the question about the solution's reliability and robustness when the assumption or some parameter is changed. Third, this research does not present the practical implications and steps for implementation in real environments. Future research will test the proposed solution in real environments and situations.

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