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Quantification of students' active learning in design, build, and test engineering modules

The focus in this paper is to address the primary research question 'How can instructors leverage assessment tools in design, build, and test modules to quantify students' active learning well enough to improve modules for future students?' In the engineering module, Product Design Group Project (PDGP), the primary goal is to enable students to internalize five principles of engineering design (POED), wherein each assignment students are tasked with writing learning statements (LS). LS captures how much students internalize the target POED and formulate an understanding of how to apply this knowledge moving forward. Each academic year in the PDGP module, at a university in north-west England, around 780 LS are consented by module students. In this paper, a flexible text mining framework is used to process LS and analyse students' learning and improve the delivery of design, build, and test engineering modules, such as the PDGP.

Keywords: active learning, learning statements, text mining, self-reflection, assessment tool

Introduction

In the dynamic environment surrounding the fourth industrial revolution, there is a need for a digital workforce of tomorrow (Jiao et al., 2021) where engineers with up-to-date skills will be able to recognize and adapt to constant change (Mistree, 2013). To prepare third-year undergraduate students (UG) for their future careers as junior engineers there is a need for continuous improvement of the curriculum (Peng, Ming, Allen, Siddique, & Mistree, 2020). The future of higher education is in the connected framework that aims to bring closer university research and student education and make better connections between academics, students, and 'real world' communities (Fung, 2017). One such module is the Product Design Group Project (PDGP) designed to prepare third-year undergraduate students to make a transition to their future careers in engineering through experiential learning. The PDGP module aims to empower students to participate in active learning in an immersive authentic environment. The adopted hypothesis is by enabling engineering students to reflect on experiences related to Principles of Engineering Design (POED) and articulate their learned lessons

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they will be able to gain confidence, implement their knowledge and skills in their future working environment, and adapt to new dynamic conditions (Turns, Newstetter, Allen, & Mistree, 1997). It is contended that current evaluation methods used by instructors in design, build, and test engineering modules often focus on project output and inadequately allow instructors to assess student internalization of learning. Hence, in each PDGP module assignment students are tasked with writing Learning Statements (LS) as a team and individually. LS is anchored in an Authentic Immersive Experience structured as a triple 'Experience' followed by 'Learning' followed by 'Value' furthering a career-sustaining competency expressed as a single sentence, see Table 1. LS allows students to reflect on their experiences and identify key lessons they learned. This activity captures how much the student internalizes the target POED and formulates an understanding of how a student can apply this knowledge in their education and later in their careers.

Table 1 Structure of the learning statements (Autrey et al., 2016)

Experience x	Learning y	Value/Utility z
Through **x** (From **x**, By doing **x**, …)	I learned **y**	
I did not consider **x** initially	I realized **y**	Value/ utility **z**
I thought (expected) **x** before/ initially	I found out **y**	In future of
	I discovered **y**	Learning **y**
	I became conscious of **y**	

On average there are around thirty students attending the PDGP module each year. At the end of the module, around 750 individual LS and thirty teams' LS are collected from the students. LS is further analysed by module coordinators allowing them to understand what students learned and to identify a discrepancy between the planned and achieved outcome of the module. This information will provide insights into the state of the module and what improvements are further needed. In the first year of the PDGP module, assessing students' LS is done manually. However, the disadvantage of this approach is dealing with a huge amount of text-based data – 780 LS altogether – which is labour-intensive, time-consuming, and impossible to maintain consistency in an assessment.

In this paper, a flexible text mining (FTM) framework used to quantify students' active learning embodied in LS is proposed. The team LS used for text mining is written by PDGP engineering students in the academic year 2020 to 2021, where the module is delivered in the hybrid mode under Covid-19 restrictions. Ethical approval for this research is obtained and the ethical implications of maintaining privacy, safety, anonymity, and confidentially of the participants and following the U.K. Research Integrity Office (UKRIO) guidance on good practice in research ethics are considered. In addition, the secondary questions disseminated from the primary question are addressed:

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1) Can text mining be used in engineering education to support module coordinators in quantifying students' active learning embodied in learning statements?
2) What can be inferred by text mining the data and insights from the learning statements?
3) Can student learning outcomes be improved, and student learning assessed to improve module for future students?'

In general, the research conducted and presented in this paper is complementary to conventional forms of assessment, such as marking, used in engineering design modules and could be applied to other project-based learning modules from other fields that use reflections as a method of assessment.

The rest of the paper is organized as follows. A critical review of the related work is presented providing the evidence that text mining is the right approach in assessing students' active learning. Next, the framework is presented with functionalities and user interfaces and then the results generated by the proposed FTM framework are verified. Finally, the closing remarks are presented.

Literature review

In this section, Question 1 is addressed where the pedagogical foundation of the PDGP module and different assessment techniques in design, build, and test engineering modules are outlined. Furthermore, we justified the use of text mining approach in engineering education and identified the need for flexible approach in the assessment of PDGP module.

Pedagogical foundation of the PDGP module

The PDGP module is grounded in the triple construct of Kolb's experiential learning model (Kolb, 2014), and Dym's problem-based learning (Dym, Agogino, Eris, Frey, & Leifer, 2005), and competency-based education (Mistree, 2013). In addition, the PDGP module is built on the work of others. For example, (Mistree, Allen, Karandikar, Shupe, & Bascaran, 2002) provided a guideline for project-based learning modules. Further, Autrey, Mistree, and Siddique (2016) identified that there is a discrepancy between what students learned expressed as LS and the performance of the students in the module measured by conventional evaluation metrics such as design project output and module grades. Turns and co-authors (1997) illustrate that writing learning essays enable instructors to provide direct feedback to the engineering students and use gained insights to modify the module for future education. Moreover, (Allen, Crossley, & McNamara, 2015) demonstrate that the integration of learning essays enables students to become reflective learners. Mistree (2013) indicates that ability to adapt is the primary competency needed by engineering graduates due to the rapidly changing global environment.

The PDGP module is structured around five competencies identified by other authors (Brumm, Hanneman, & Mickelson, 2006; De Graaff Ravesteijn, 2001; Laingen,

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2014; Male, Bush, & Chapman, 2011) that will help undergraduate students to develop the ability to adapt. For example, Brumm and co-authors (2006) identified fourteen developing workplace competencies that have an impact on experiential student learning and provide students with a clear map needed to become successful engineers. Laingen (2014) demonstrated how paired supervisor assessments and students' self-assessments are useful in evaluating student demonstration of fifteen workplace competencies in an experiential learning environment and support continuous improvement of the programme curriculum. Male and co-authors (2011) indicate that developing technical, non-technical, and attitudinal competencies in engineering education is necessary. They identified eleven competency factors required by engineers graduating in Australia that would assist the evaluation and improvement of engineering programmes. De Graaff and Ravesteijn (2001) indicate that engineering education is changing with demand from industry and that a new set of educational tools is required.

Assessment in design, test, and build engineering design modules

Autrey et al. (2016) identified that there is a disparity in how module coordinators evaluate engineering design modules and what students learned expressing the need to improve assessment instruments. Smith, Siddique, and Mistree (2014) discussed how student performance improves when they are required to perform critical self-assessment. Other authors identified the need not only to improve assessment instruments but also the importance of students' self-assessment process in obtaining module competencies (Besterfield-Sacre, Atman, Shuman, 1998; Segers & Dochy, 2001). Olds, Moskal, and Miller (2005) presented a catalogue of assessment instruments for engineering educators along with self-assessment for students. However, some authors stressed the importance of utilizing LS as one of the instruments to assess students' active learning (Autrey et al., 2016; Autrey, Sieber, Siddique, Mistree, 2018; Peng et al., 2020).

Text mining in educational research

There is a growing number of educational applications of text mining to find useful knowledge for educational stakeholders (Ferreira-Mello, André, Pinheiro, Costa, & Romero, 2019). The most prevalent text mining methods and techniques used in education are text classification and natural language processing.

Text classification and clustering. The most used algorithms for text classification and clustering are Support Vector Machine (SVM) and K-means, along with neural networks (Ferreira-Mello et al., 2019). In education text classification is used for the automatic classification in common module tasks such as lectures, class discussions, and student group work (Wang, Pan, Miller, & Cortina, 2014); and the categorization of forums discussion in topics (Tobarra, Robles-Gómez, Ros, Hernández, & Caminero, 2014). Student clustering is used to improve text prediction (Trivedi, Pardos, &

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Heffernan, 2011), measure engagement (Liu, Calvo, & Pardo, 2013), identify learning patterns (Cobo, García-Solórzano, Santamaría, Morán, Melenchón, & Monzo 2010; Mansur & Yusof, 2013), improving recommendation system for educational resources.

Natural Language Processing (NLP). Educational platform has accepted NLP for automatic evaluation of essays, such as text cohesion (Balyan, McCarthy, & McNamara, 2017) and written argumentation (Elouazizi et al., 2017), and open questions, such as evaluation of students' answers (Cutrone & Chang 2010) and generates new questions (Flor & Riordan, 2018), where evaluation is improved by adopting text mining (Crossley, Allen, Snow, & McNamara, 2015). NLP is further adopted to enrich interactions, such as collaborative work on chats (Trausan-Matu, Dascalu, & Rebedea, 2012), predict group project performance (Yoo & Kim, 2014), and predict interactions based on past discussions (Kim & Shaw, 2014).

Text mining application in education is versatile where the most popular are evaluation, student support, and analytics (Ferreira-Mello et al., 2019). It is usually used for analysing a massive volume of data providing support to module coordinators, and to keep students informed and motivated, and preventing dropouts by providing support to students in their education. It can be concluded that it is useful in generating and analysing LS in the PDGP module due to the sheer size of the data.

Critical review of related work

Frasciello (2015) outlines a model for text mining of student writing samples in engineering modules where he analyses how the quality of student writing is shaped by higher degrees of contextualized instruction. Furthermore, Autrey and co-authors (2018) use a two-pronged method for evaluation of the LS using POED categorization and the zero-three point 'insightfulness' scale to analyse student writings. Peng and co-authors (2020) proposed a text mining framework to facilitate the analysis of a vast number of LS obtained by engineering students and text quantification method, text similarity, to facilitate instructors gaining new insights from students' LS (Peng et al., 2020). Sun et al. (2021) propose a Latent Dirichlet Allocation algorithm to analyse students''Takeaways (TA)' and to relate the takeaways data to instructor's expectations using text similarity.

In the PDGP module, students are required to write TA in the context of an Authentic, Immersive Experience that is further analysed and transferred to LS. However, many students fail to make that transition from TA to LS due to various reasons. For example, failing to follow the triple experience/learning/value structure, their LS are not grounded in POED, or some elements of the triple structure are identified but not all of them. Other authors in their work assumed that to analyse LS obtained by engineering students each student needs to write a triple structure experience/learning/value single sentence LS for each assignment (Autrey et al., 2016; Autrey et al., 2018; Peng et al., 2020). However, after closely working with engineering students the author recognized that there is a need for a flexible framework to analyse both LS and TA while supporting module coordinators to gain new insights from students' LS as presented in the next section.

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Methodology

In this paper, a design approach Flexible Text Mining Framework (FTM), from the user's perspective, is proposed. There are two types of users of the FTM framework, data contributors and researchers, respectively red and green charts in Figure 1. Data contributors are students who submit original assignment submissions with Takeaways (TA) or Learning Statements (LS) and teaching assistants or module coordinators who collect and upload submissions to the FTM for analysis. Researchers are sole module coordinators who quantify students' active learning. By exercising FTM the researchers can answer some specific questions: 'What is the reason for student-teams low performance? Where are the bottlenecks in the module? What are the features of the team? What knowledge is common, different, or missing among teams?'

The FTM framework consists of three parts, data contributors, programme, and researcher, respectively red, brown, and green charts in Figure 1. Data contributors have a task to provide data sources to the programme, which includes 1) submitting original documents to the programme, 2) setting targeted learning POED for each assignment, 3) setting up matching rules for the extraction of TA or LS, and 4) annotate relevant attributes to the uploaded documents. The programme has four main functionalities: 1) data cleaning to extract keywords from the raw textual contents, 2) data management to save the cleaned data into the database using structured formats, 3) text analysis to analyse the stored textual data and discover the hidden patterns using various of algorithms, and 4) visualize results by using different types of graph or charts to facilitate researchers gaining insights from the textual data. The visualized analysis results can support the researcher's insights to interpret the original text contents, answer research questions, and identify the next step or action that needs to take place as a result of the research.

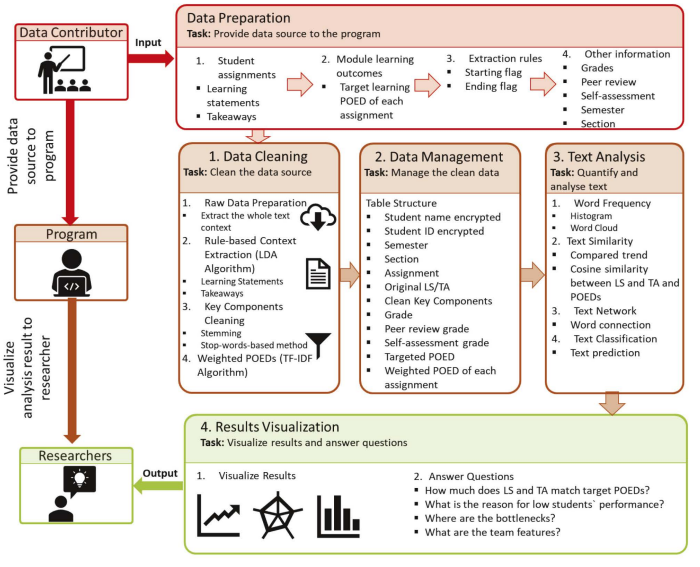


Figure 1 The flexible text mining framework for quantification of students' active learning

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The four functionalities of the programme are discussed in the following sub-sections.

Function 1: Data cleaning

The LS or TA submitted in an assignment are sentences consisting of nouns, verbs, adjectives, adverbs, prepositions, and conjunctions. Prepositions and conjunctions are the words used to maintain continuity of the sentence, and in the context of this research are impractical. Nouns, verbs, adjectives, and adverbs give insights into students' learning and in the context of this research have practical meaning and the sentences are cleaned to keep meaningful components. The function of data cleaning has four steps.

- In Step 1 raw data is prepared where students voluntarily submit their LS or TA after completion of the module. The LS have [Experience|Learning|Value] triplet structure, as presented below in the example.

> Through the discussion of Computer-aided design (CAD), I learned the importance of incorporating CAD modelling in the design process which will be useful for me to create a strong design in a more efficient manner.

The TA are unstructured sentences that have some elements of the learning statement Experience or Learning or Value, as presented below in the example.

> A design process can be extremely helpful for decreasing development time and increasing product quality that I can use in my future design career.

Afterwards, the LS or TA are uploaded in the text mining programme with other information (lecture information, problem description, solutions) archived as one document by the teaching assistant or module coordinator.

- In Step 2 the rule-based content is extracted where Linear Discriminant Analysis (LDA) algorithm is used to extract LS or TA from the archived document from Step 1. Some examples of located LS are as follows:

Learning Statement:	*Through the discussion of CAD,…*
Learning Statement 1…n:	*Through the discussion of CAD,…*
Individual Learning Statement:	*Through the discussion of CAD,…*
Team Learning Statement:	*Through the discussion of CAD,…*

The position of the LS or TA in the archived document is located based on the phrases 'Learning Statement, Learning Statement 1…n, Individual Learning Statement, Team Learning Statement'. These phrases can be picked up by setting up the matching rule followed by the extraction of the whole sentence. The extraction is terminated when it reaches a period or a linefeed.

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- In Step 3 the key components are cleaned where the programme will filter unusable words and characters from the textual contents using the stemming and stop-words-based method. In this research, the stemming method is used to convert all the meaningful components to their root form. Stop words are filtered out before processing natural language data, in our case text. Furthermore, the stop-words-based method is used to filter out syncategorematic words, such as 'the', 'a', 'of' that do not stand alone in the sentence.
- In Step 4 the POED are weighted where the TF-IDF algorithm is used to extract a set of keywords representing each POED. The module coordinator can assign different weights to each targeted learning POED. For example, in Assignment 1 *Planning a Design Process* module coordinator can issue a higher weight to POED 1c *Understanding the problem* than POED 1d *Proposing a plan of action* once students understand the problem then they can identify tasks needed to address the problem and in which time frame (or propose a plan of action).

Function 2: Data management

Submitted LS or TA can contain many attributes, such as the name of the student, the name of the team, the academic year, and semester when the LS or takeaway is generated, the phase of the design process taught by the module coordinator, and the number of the assignment. Attributes are valuable for future evaluation especially when a vast number of LS are accumulated. In Table 2, the data structure for the PDGP module is presented used to capture the associated attributes and permanently store the attributes along with LS in a database.

Table 2 Specification of attributes for data management

Attribute	Explanation
Student name encrypted	Captures the encrypted student name.
Student ID encrypted	Captures the encrypted student ID.
Academic year and semester	Captures the academic year and semester to which the learning statement belongs, for example, AY202021, Fall2020, etc.
Section	Captures the section to which the learning statement belongs, for example, Section 001 (Taught by Instructor A), Section 002 (Taught by Instructor B), etc.
Assignment	Captures the assignment from which the learning statement was generated, for example, Assignment 1 (Team Formation), Assignment 2 (Conceptual Design), etc.
Original learning statements or takeaways	Captures the original learning statements or takeaways before it is cleaned.
Clean key components	Captures the key components of the learning statements or takeaways after it is cleaned.

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Attribute	Explanation
Grades	Captures the grade given by the instructor or teaching assistant in terms of the student's performance in the assignment.
Peer review grades	Captures the grade given by the peers in terms of the peer's performance in the assignment.
Self-evaluation grades	Captures the grade given by the students in terms of their performance in the assignment.
Targeted POEDs	Captures the targeted POEDs before weighting.
Weighted POEDs	Captures the weighted targeted POEDs.

Along with the LS, the module coordinator can submit targeted learning POED that are weighted to identify matching degrees between LS or TA and targeted learning that takes place in the next step.

Function 3: Text analysis

In the LS or TA, there are many hidden patterns. Patter is the occurrence frequency of some words, such as in team LS the word 'team', 'project' appears often and in individual statements the word 'I' appears often. Another pattern is associated with higher grade students, their LS are a closer match to the target learning POED. Also, there is a correlation between individual LS or TA and how they change with a different phase of the design process. These patterns are identified by quantifying the text. In the text mining programme, the Term Frequency (TF), Inverse Document Frequency (IDF) measures how important a term is in a document, word vector, and text similarity as text quantification methods are used, as presented in Equations 1–4.

$$Term\ Frequency: TF(t_i, D_i) = N(t_i, D_i)/\|D_i\| \quad (1)$$

where $t_i(i = 1 \cdots n)$ is specific term, $D_i(i = 1 \cdots n)$ is specific document that contains term t_i, $N(t_i, D_i)$ is the number of times term t_i occurs in document D_i, and $\|D_i\|$ is the total number of terms contained in the document D_i.

$$Inverse\ Document\ Frequency: IDF(t_i) = 1 + \log\left(\frac{DF(t_i)}{N}\right) \quad (2)$$

where N is the total number of documents, $DF(t_i)$ is the number of documents with term t_i.

$$Computing\ Result\ of\ a\ Term\ in\ the\ Document: TF - IDF(t_i) = TF(t_i, D_i) \cdot IDF(t_i) \quad (3)$$

$$Word\ Vector: Vector(D_i) = [TIt_i], i = 1 \cdots n \quad (4)$$

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where TIt_i is computing result of a term in the document, $Vector(D_i)$ is the vector of the document embodied by all terms of $TF - IDF(t_i)$ values.

$Text\ Similarity$: (5)

$$TS(D_i, D_p) = cos < Vector(D_i), Vector(D_p) >= \frac{Vector^T(D_i) \cdot Vector(D_p)}{\|Vector(D_i)\| \cdot \|Vector(D_p)\|}$$

where $TS(D_i, D_n)$ stands for similarity between document D_i submitted by students and document D_p weighted targeted learning POED submitted by module coordinator measured by cosine value of the two texts.

Function 4: Data visualization

The visualization of analysed data is displayed intuitively so the hidden patterns in the LS or TA are visible to a researcher for gaining further insights. In the FTM framework, different graphical tools, such as tag cloud, histogram, line chart, text network, or scatter plot are explored. A line chart is used to show the evolving trend of a particular feature of LS or TA and to show the similarity rate between LS or TA and targeted learning outcomes (POED). A text network is useful for data analysis and topic modelling, wherein text analysis the words are the nodes, and the co-occurrences are the relation between them. With the use of graph theory, different patterns and insights into the text structure can be discovered. In this paper, the text network is used to discover the most influential or common words teams use in LS or TA, the structure module or different words, and the structural gaps or the missing words in the LS or TA (Autrey et al., 2018; Peng, et al., 2020; Wu, Ming, Allen, & Mistree, 2022).

Results and discussion

In this section, the requirements of the PDGP module, LS and Takeaways (TA) as an active learning tool are presented. Furthermore, Question 2 is addressed followed by a discussion of what can be inferred by text mining data and what insights can be obtained from the active learning tool.

The requirements of the PDGP module

In the PDGP module, the primary goal is to enable students to internalize five POED that are relevant to modules that involve the design, build, and test of a product and to hit the ground running as junior engineers upon graduation. In the PDGP module, students must complete a two-semester design, build and test project with a team of their peers. In this module, the focus is on learning and not only on how well the project device performs on the day of the demonstration. By the time students' group design project is finalized, students must develop abilities to internalize related POED

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associated with key design stages, namely, 1) planning a design process, 2) preliminary design, 3) embodiment design, 4) prototyping and testing, and 5) learning through doing, reflecting, and articulating. Specific POED of each design phase with underline keywords is presented in Figure 2.

1. **Planning a Design Process**
   a. Forming a **team**
   b. Accepting and executing a **team contract** to stipulate ethical guidelines to **decision** making and **problem** resolution
   c. **Understanding** the **problem** and framing the problem statement
   d. Proposing a **plan of action**
2. **Preliminary Design**
   a. Ideating and generating **concepts**
   b. Developing **concepts** to ensure functional **feasibility**, ensure **realizability** (technical feasibility)
   c. Evaluating the **concepts** (functional feasibility, technical feasibility) and identifying that system concept which is most likely to succeed
3. **Embodiment Design**
   a. Refining/modifying the most likely to succeed **concept** through technical **analysis**, **experimentation** and **thought exercises**
   b. Stipulating available **assets**
   c. Ensuring functional **feasibility**, technical feasibility, realizability (buildable within **budget** and with available **skills**), and **safety**
4. **Prototyping and Testing**
   a. Creating a **bill** of **materials** as built, including an understanding of the **limitations** and capabilities of the chosen components
   b. Ensuring that the **design** as built meets **target performance** requirements
   c. Performing a **critical analysis** after device **prototyping** of causes of success and failure
5. **Learning through Doing, Reflecting, and Articulating**
   a. Critically **evaluating** the **processes** of designing, building, and testing
   b. Articulating, using **learning statements**, the Principles of Engineering Design that you have internalized
   c. Identifying new **POEDs** and carrying that knowledge into future projects and experiences

Figure 2 Target POED in the PDGP module

Four assignments are developed to help students internalize the POED. The scaffolded structure maps the targeted POED to the specific assignments in which they appear, see Table 3. For example, in the first assignment (Column 2 in Table 3) given that the project is introduced to students as a story from the user perspective (persona) along with the team contract students are required to provide a Problem Statement, Plan of Actions, House of Quality, Requirements List, and the Learning Statements or Takeaways. For these assignments, explicit instructor learning target POED includes 1a, 1b, 1c, 1d, and 5b. However, it should be noted that students may reflect on the connection between assignments and the target POED that are not explicitly mentioned in Table 3. After comparing text mining results and information from Table 3 it can be identified whether students' learning in each assignment meets the target POED (Wu et al., 2022).

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Table 3 Structure for scaffolding the POED and the PDGP course assignments

Assignment	1	2		3	4
Part		Part 1	Part 2		
Description **Target POED**	***Given:*** Story (Persona), TC ***Provide:*** PS, PoA, HoQ, RL, LS	***Given:*** PS, PoA, HoQ, RL, LS ***Provide:*** FS, MC, 6 Concepts, PMI, Failure, LS	***Given:*** FS, MC, 6 Concepts, PMI, Failure, LS ***Provide:*** Go/No-Go, P&B Concepts, BoM, Selected Concept, LS	***Given:*** Selected Concept ***Provide:*** GA, CAD model, refined BoM, RA, LS	Project summary report, demonstration, placing product on market (plan of action)
1a	✓				✓
1b	✓				✓
1c	✓				✓
1d	✓	✓	✓	✓	✓
2a		✓			
2b		✓			
2c		✓			
3a			✓	✓	
3b			✓	✓	
3c			✓	✓	
4a				✓	
4b					✓
4c					✓
5a					✓
5b	✓	✓	✓	✓	✓
5c					✓

Learning statement and takeaways as a 'Learning through Reflection on Doing' tool

In the PDGP module students are required to learn by reflecting on doing authentic immersive experiences that require the understanding and translating of customer requirements into technical specifications, defining the architecture of the prototype, and building and testing the device under competitive conditions. In the context of an

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Authentic, Immersive Experience they write Takeaways that they further analyse. First, they need to identify the 'Value' which helps them grow (gain / further a competency) as a junior engineer. Second, they need to reflect backwards by answering the following questions 'What "learning" is foundational to my attaining this value?', 'What "experience" is foundational to this lesson I learned?' Finally, they write forward a learning statement, a triple experience/learning/value as a one-sentence while highlighting transformative words/phrases (Peng et al., 2020). However, sometimes students fail to make a full transition from TA to LS, and the information captured within TA is valuable and as such should not be discarded (Wu et al., 2022).

Text mining of the PDGP learning statements and takeaways

The average sentiment value is presented in Figure 3, where the X-axis represents Assignment, and the Y-axis represents the average sentiment value of all the learning statement in a specific assignment. From the line chart diagram, it can be seen the team with a low sentiment value has a low frequency of the keywords and the team with a high sentiment value has a high frequency of the keywords, respectively Teams 2 and 3 for Assignment 1 (CW1).

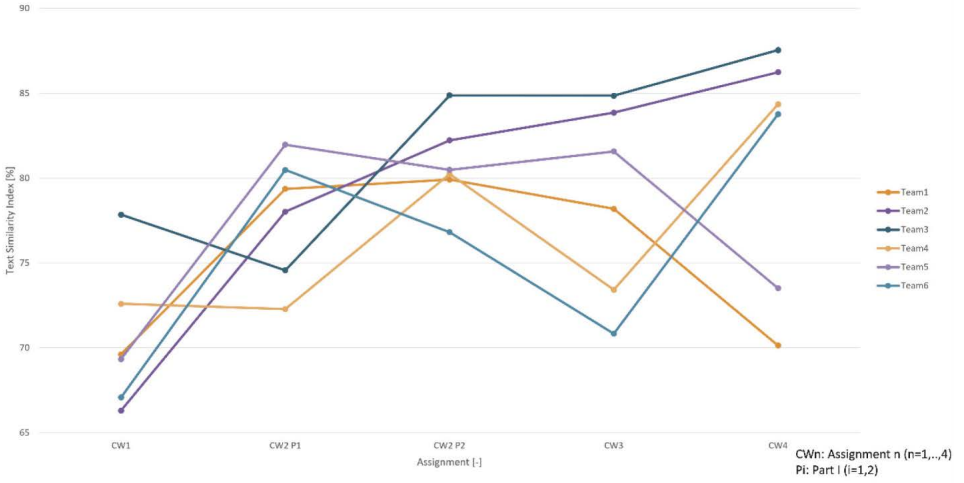


Figure 3 Average sentiment value of the POED in the PDGP module assignments

We compared the average sentiment value index and the average marks across the assignments to determine is there a discrepancy between students' internalization of POED and application of that knowledge; see Table 4. Although, this discrepancy, measured as standard deviation, is present throughout the assignments it reaches a critical point around embodiment design, see Assignment 2 Part 2 in Table 4. This variation indicates the lack of either internalization of POED or application of that knowledge that has a potential impact on the remaining of the design process.

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Table 4 Standard deviation between average sentiment value and average marks in the PDGP module assignments

	Assignment 1	Assignment 2 Part 1	Assignment 2 Part 2	Assignment 3	Assignment 4
Average sentiment value	70.47	77.78	80.76	78.79	80.92
Average marks	64.17	68.50	67.33	67.33	69.83
Standard deviation	4.46	6.56	9.50	8.10	7.85

The relationship between the average sentiment value and the average marks across the assignments is investigated to determine the reason for the discrepancy between students' internalization of POED and the application of that knowledge. As a result, the different features of the teams emerged that are further clustered into three types based on their level of internalization of POED and the application of that knowledge, see Figure 4. For example, Type 1 has a high level of internalization of POED, see dashed orange line in Figure 4a), and a low level of application of that knowledge, see solid orange line Figure 4a). Type 2 has a moderate level of internalization of POED, see dashed purple line in Figure 4b), and a moderate level of application of that knowledge, see a continuous purple line in Figure 4b). Type 3 has a low level of internalization of POED, see dashed green line in Figure 4c), and a high level of application of that knowledge, see continuous green line in Figure 4c). Hypothesis is that with further improvement of the module, the teams would have a high level of internalization of POED knowledge and a high level of application of that knowledge where the text-similarity index and students' grades would be identical line charts.

After taking look at the overall trend of students' sentiment values, and different level of internalization of target POED and application of that knowledge the following question is posed 'What words are commonly used by the teams or what words contribute to sentiment values?' First, through text network analysis of sentiment words (whose semantic valence is not zero) that appear the most frequently in the LS or TA and their semantic relation in text the similar, different, and missing nodes are identified. In Figures 5 and 6, a network generated by the VOS viewer is presented (Van Eck & Waltman, 2007). In Figure 5, sentiment words with high frequency are divided by their lexical meanings appearances in the sentences revealing what type of words benefits sentiment values in Figure 3. The size of the circle presents the word frequency and the colour represent different topic groups. The dominant topic group with high frequency are 'learn', 'design', and 'concept', therefore, the conclusion is that teams' common focus is on the design process, concept generation, learning POED (see Figure 5). Less dominant topic group with lower frequency are 'management', 'method', 'evaluation', 'decision', therefore, the conclusion is that the teams have a different

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focus on management style, design method, evaluation, and decision-making (see Figure 6). In addition, missing topic group with high frequency is identified 'manufacturing', 'knowledge', 'assembly', 'failure' indicating that there is a missing knowledge on manufacturing, building knowledge, assembling, and failure estimation of post-mortem analysis (see Figure 6). This lack of knowledge of manufacturing methods, technologies, and processes required for the final stage of the design process, in Assignment 4, can be associated with hybrid mode of learning and Covid-19 restrictions. These restrictions resulted in a lack of on-site classes and workshop experience, where physical prototypes are replaced by virtual prototypes, stripping off students' valuable 'build and test' experience.

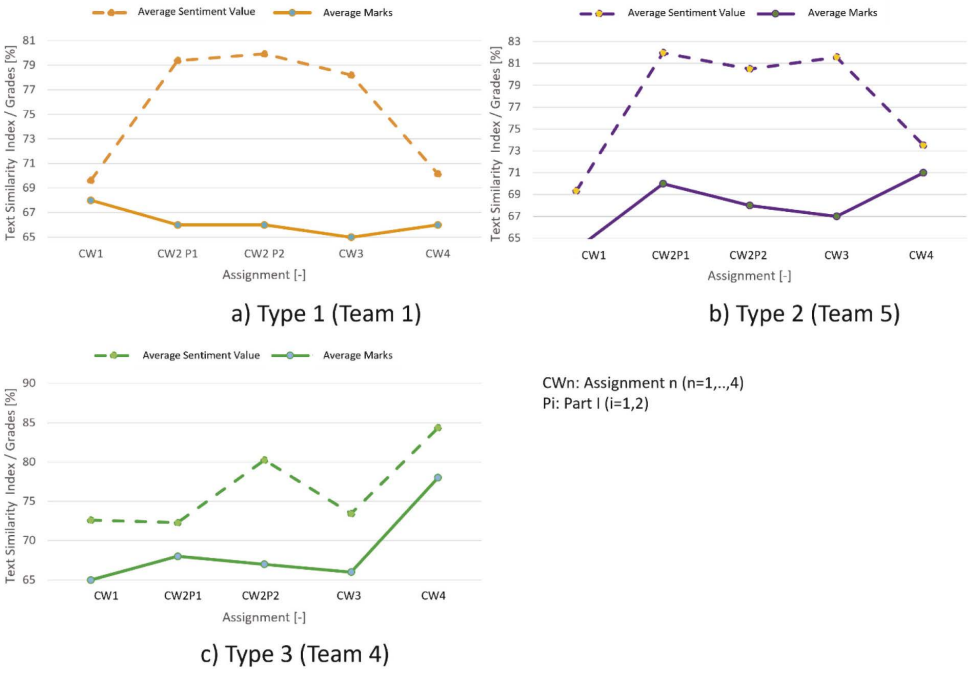


Figure 4 The features of the teams in the PDGP module, a) Type 1, b) Type 2, and c) Type 3

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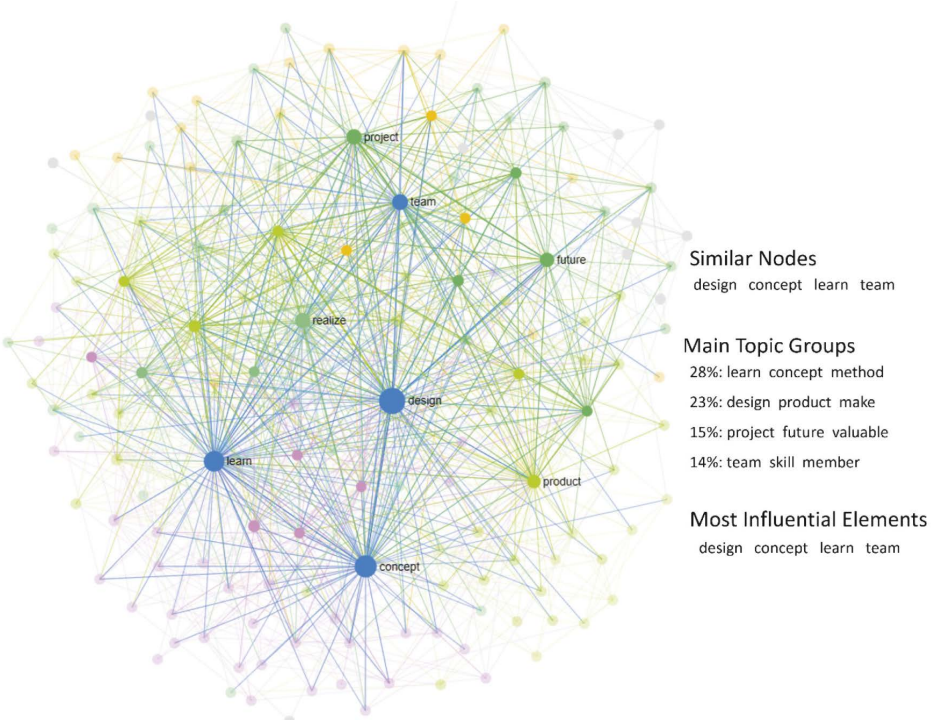


Figure 5 Text network of similar nodes of the PDGP teams

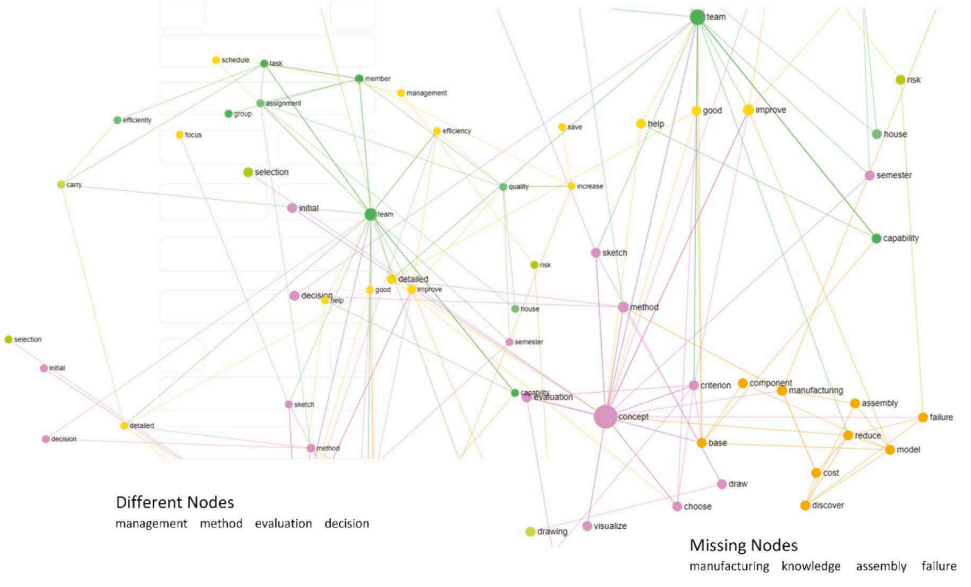


Figure 6 Text network of different and missing nodes of the PDGP teams

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Contributions, limitations, and implications of practice

In this section, Question 3 is addressed followed by a discussion what these findings might mean to other researchers or other fields. We are confident that the use of a FTM framework to interpret student LS or TA in this work provides useful information regarding patterns in the student learning and internalization of the module material.

Contributions of this research

- The FTM framework can support a researcher to identify where a discrepancy between students' internalization of POED and application of that knowledge appears so the researcher can act early on to avoid propagation of this variation through the remainder of the design process. For example, specific bottlenecks are identified in the design process around Embodiment Design (Assignment 2 Part 2), see Table 4. Embodiment design is a critical transfer point in the design process from a principal solution to a detailed design that can lead directly to production. As such, the module instructor needs to pay attention to this part of the design process to reduce the gap between the internalization of POED and the application of that knowledge. Currently, in the PDGP module preliminary and embodiment design are under Assignment 2. This result indicates that these two phases of the design process need to be treated as separate assignments.
- Identify different features of the team indicating that not all teams internalize or apply knowledge at the same level. This creates an opportunity for researchers for authentic module delivery and assessment. For example, it is identified that teams are heterogeneous with different nodes of focus, such as management style, design method, evaluation, and decision-making, which leads to the conclusion that there is a need for authentic assessment of the teams to truly quantify the internalization of POED and application of that knowledge.
- Identifying common, different, and missing knowledge among teams' gives opportunity for researcher to identify the next step or action that needs to take place as a result of the research. For example, Missing knowledge is the Prototyping and Testing phase where missing nodes in students' manufacturing knowledge are identified through text network as presented in Figure 6. It is identified that this missing knowledge is due to Covid-9 restrictions and a lack of on-site active learning in workshops and design studios. For future generations this gap should be substituted with the appropriate computer-aided design (CAD), computer-aided manufacturing (CAM), and finite element analysis (FEA) tools.

Limitations of this research

In this paper, the team LS and TA are analysed and presented. The limitation of the FTM framework is the inability to assess individual internalization of POED and application of that knowledge in the group design project. However, this framework can be used for the assessment of individual students' learning in individual design projects.

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Furthermore, as FTM is based on text mining where more data is required from different cohorts throughout years to take full advantage of sentiment value analysis and text network analysis indicating the module improvement or deterioration (Wu et al., 2022). In addition, the FTM framework is applied at the end of each module once students' final marks are submitted. Only after data is analysed specific actions that need to be undertaken are identified so the module can be improved for a future generation of students. To fully answer Question 3, the data from the next generation of students needs to be analysed and compared with data from this generation to determine if the students' learning improved.

Implication to other researchers or other fields

This analysis might be useful as a complement to conventional forms of assessment, such as marking, used in engineering design modules. Currently, in conventional engineering design modules students are graded based on how well they solve the design challenge. The only measurable outcome is the design reports, the design mechanism, and its performance, which is not an appropriate or adequate metric to assess student learning (Autrey et al., 2018). Unlike the method explored in this paper, evaluation of the design artefact does not facilitate an understanding of how students learn in a design project, how insightful that learning is, or how it changes in response to particular tasks (such as assignments).

In general, the research conducted and presented in this paper can be applied to other project-based learning modules from other fields that use reflections as a method of assessment.

Closing remarks

In this paper, the FTM framework is introduced and implemented to partially answer the primary question 'How can instructors leverage assessment instruments in design, build, and test engineering modules to quantify students' active learning well enough to improve modules for future students?'

In Question 1, we ask 'Can text mining be used in engineering education to support module coordinators in quantifying students' active learning embodied in learning statements?'. Through surveying relevant literature, the importance of utilizing LS as one of the instruments to assess students' active learning is confirmed. Furthermore, we justified why text mining is an appropriate process when generating and analysing a large number of LS. However, since many students fail to make the transition from TA to LS we identified the need to generate and analyse both; therefore, we proposed new FTM framework to quantify students' active learning and answer Question 2.

In Question 2, we ask 'What can be inferred by text mining the data and insights from the learning statements?'. After exercising the framework and analysing the data the following is the outcome:

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- Quantify students' active learning, the level of understanding and internalization of the target POED and to what extent they implemented obtained knowledge in the design process.
- Identify the bottlenecks in the design process that can limit the students' active learning.
- Identify the missing knowledge in the design process, such as manufacturing methods, technologies, and processes due to Covid-19 restrictions. This raised the need for CAD/CAM/FEA software tools as an appropriate substitute for a workshop experience.
- The need for an authentic assessment due to heterogeneity of the team and different needs.

Overall, while we are confident that, within the scope of this paper, the text mining approach has enabled us to satisfactorily resolve Question 2, in the future, we will likely focus on further analysing the text mining results.

In Question 3, we ask 'Can student learning outcomes be improved, and student learning assessed to improve modules for future students?'. The FTM framework supports researchers to gain insights, interpret the original text contents, answer 'why' questions, and identify the next step or action that needs to take place as a result of the research. In this paper, we made a few recommendations for the improvement of the PDGP module for future students. However, after analysis and comparing the data from this year's and the next year's cohort of student only then we will know the level of improvement in student learning and would answer the Question 3 completely.

In conclusion, the FTM framework is of relevance to different stakeholders, such as students, educators, and researchers. For example, it can be augmented for students to get timely feedback on their submissions enabling them to self-correct and self-learn, educators can gain insights enabling them to improve modules for future generations, and researchers can use it as a foundation for future text mining methods.

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Quantification of students' active learning in design, build, and test engineering modules

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