Quantification of Knowledge Exchange within Classrooms: An AI-based Approach

Omar Elnaggar, University of Liverpool, United Kingdom
Roselina Arelhi, University of Sheffield, United Kingdom

The European Conference of Education 2021
Official Conference Proceedings

Abstract
Knowledge management improves efficiency and productivity of a company. A typical knowledge transfer pipeline, an enabler of knowledge management, consists of academics, higher education institutions, research funding bodies and companies. While the knowledge exchange mainstream sheds light on research collaborations, the evaluation of in-classroom knowledge exchange is often omitted, underestimating the impact this would have on the student employability. Current work on knowledge exchange at higher education institutions primarily focuses on: (i) collaborations with external parties, and (ii) identifying factors that affect knowledge sharing behaviours. This paper extends knowledge exchange to classroom teaching through: (i) formulating a framework among undergraduate Engineering students, and (ii) proposing an Artificial Intelligence based approach for evaluating the knowledge exchange process. The framework comprises of two group coursework with an intermediate handover event emulating an industrial workplace scenario in which knowledge exchange plays a key role. Then, an artificial intelligence-based visualisation technique processes data from two coursework-based surveys, completed before and after the abrupt handover event, to assess the change in the student intellectual backgrounds using two-dimensional maps embedding students as datapoints. The results interestingly reveal correlations between standard student evaluation metrics (for example grades, peer review and survey scores) and the formation of datapoint clusters. It is argued in the paper that the proposed artificial intelligence tool lends educators with tools to better understand the individual student performance in ways that are not captured by conventional academic assessments.

Keywords: Knowledge Exchange, Knowledge Transfer, Knowledge Sharing, Dimensionality Reduction, Assessment Metrics

1. Introduction

In today's era of knowledge economy, knowledge has become the main driver of economic growth. Knowledge management (KM), a term coined in the 1980s, has been recognised as a crucial factor for the survival of companies in today's dynamic environment. Explicit and tacit knowledge as assets that originate from an individual through learning or experience resides within a company for as long as the individual is, unless they are captured, stored or transferred. Hence knowledge transfer (KT) is crucial to ensure that the departure of any individual with valuable knowledge will not deprive a company of its crucial assets.

While there is a wealth of literature on KM adopted by companies, the same cannot be seen in the education sector (Asrar-ul-Haq et al., 2016). KM in the context of higher education where knowledge is often created has typically involved academics and researchers transferring knowledge to companies and the wider communities. It is only recently that students at HEIs have been included in the KT pipeline as it is recognised to enhance their employability skills enabling them to succeed in their future workplace, empowered by their ability to acquire and transfer knowledge effectively. In 2020, the *Office for Students and Research England*[1] provided funding of £10 million to twenty HEIs to explore the student involvement in knowledge exchange (KE) activities. The project aims to investigate the benefits of such activities with the business and wider community partners. On a large scale, this is a good initiative that adds undergraduate students to the KE pipeline after it was exclusive to researchers and academics only. In the literature, the student-oriented KE mainstream primarily focuses on one of the following: (i) the investigation of factors that affect knowledge sharing (KS) student behaviour, and (ii) the benefits of KE to students and external collaborators.

Many factors such as personal and group characteristics tend to affect knowledge-sharing behaviour (Asrar-ul-Haq et al., 2016). It was found that students may embrace hoarding knowledge to secure a competitive advantage over their peers (Boytsov et al., 2017; Wei et al., 2012). It is very likely that if their unwillingness to share knowledge continues, this personal trait will have a long-term impact on their future career. Mistrust and lack of self-confidence are also barriers for knowledge sharing. From a psychological perspective, it is thus imperative to cultivate knowledge-sharing habits as early as possible. Many works encouraging knowledge sharing among students involve collaborations with external partners. However, these partnerships do not directly address challenges such as lack of confidence especially when students communicate their ideas to senior staff in collaborating companies. Instead, a better way to boost confidence would be to facilitate peer-to-peer learning as students feel more comfortable interacting with each other. In fact, there are many benefits of peer learning as reported in (Boud et al., 2014).

Motivated by the benefits that peer-to-peer learning could bring, this paper proposes a KE framework within classrooms. In addition, to address the lack of methods and metrics to evaluate the effectiveness of such a framework, an Artificial Intelligence (AI) based approach is employed to help visualise the KE process on low-dimensional maps.

The remainder of this paper is outlined as follows. First, the context, methodology and assessment metrics for our proposed KE framework is presented in Section 2. This is followed by a discussion on the dimensionality reduction technique used for visualising the KE process

[1] https://www.officeforstudents.org.uk/advice-and-guidance/funding-for-providers/knowledge-exchange-funding-competition/

in Section 3. The results and metric-based analyses of the students' performance are presented in Section 4. The paper concludes in Section 5 with a summary of the benefits of the proposed approach and directions for future work.

2. Knowledge Exchange Framework

2.1 Context

There are many terms describing the enablers of KM; some are used interchangeably but with overlapping concepts. The three key terms that are used in our proposed framework are KS, KT and KE. A common demarcation between KS and KT is related to the levels of analysis where KS is more frequently used to describe knowledge on the individual level, whereas KT implies the involvement of groups of people (Argote et al., 2000; Choo, C W and Alvarenga, 2010). In the same vein, as our framework involves a group work for a module, we define KS as a multi-directional, intra-group process where members within a group share knowledge as knowledge givers and/or recipients. KT on the other hand involves a uni-directional, inter-group transmission of information, where the recipient group absorb, use and make sense of the received information. In our two-stage approach, a knowledge recipient group subsequently becomes knowledge givers by transferring their work to another group. As it will be further elaborated in Section 2.2, all groups are knowledge givers and recipients in Stages A and B respectively, hence, KT occurs as a bi-directional process which we refer to as KE.

2.2 Methodology

Students undertaking an engineering year-long module have two group coursework to complete. In a conventional group work setting, students tend to create and share knowledge primarily within their own group. On a macroscale, this means that different groups of students will end up having varying levels of understanding of the given subject. The proposed framework aims to introduce a bi-directional KT element to the learning process. Eventually, this would move the class from several isolated KS groups to a KE environment where knowledge flows within and between groups as illustrated in Figure 1.

Figure 1 illustrates the proposed framework. Group *Y* (on the right) is given Assignment A in which they need to propose a solution to a given engineering problem. Initially, intra-group KS is expected to occur as they brainstorm ideas. At the end of the assignment, they submit a report which documents their proposed solution. Their report is anonymised and passed on to Group *X* (on the left). In this respect, KT occurs through the *codification strategy* (Joia et al., 2010) as there is no interaction between the knowledge givers and providers and the transferred information is contained in an object; the group report in this case.

Before handing the report to Group X, the recipient members are first asked to complete a survey that tests their knowledge on the given engineering problem of Group *Y*. Afterwards, Group *X* is provided with the report, makes sense of the information provided, evaluates the feasibility of the proposed solution, and devises a management plan for carrying out the project. In other words, following the KT from Group *Y* to Group *X*, KS re-occurs within Group *X*.

After Group X finishes their coursework, they are asked to complete the same survey once again by the time they submit their own report. Completing the same survey twice enables the evaluation of how much each member have benefitted from KT. From an industrial perspective, this allows for measuring the absorptive capacity of students, a notion introduced by (Cohen et al., 1990) which defines the ability of an employee to recognise the value and capitalise on external information, and apply it to the problem in hand. Ideally, through a successful KE framework, the student scores will be higher in the second survey.

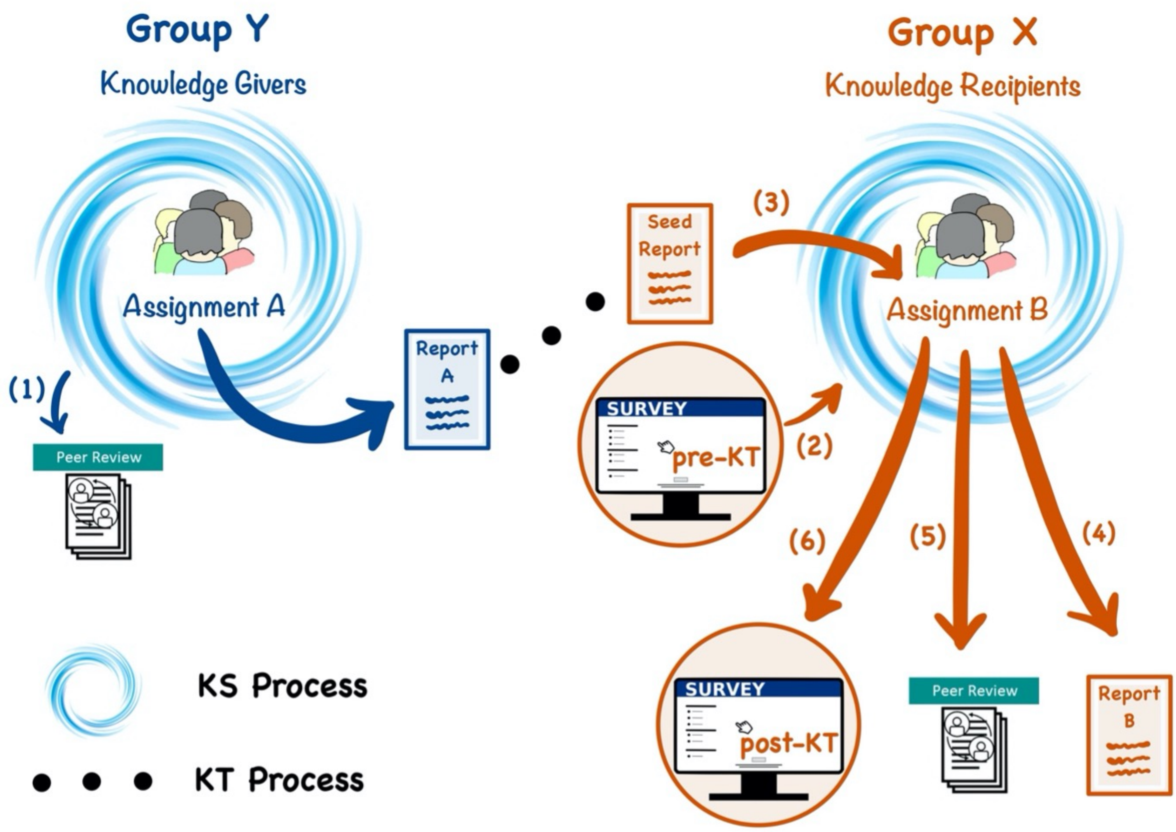


Figure 1: The Proposed KE Framework for an Undergraduate Engineering Group Work (Only One-Way KT Is Illustrated for Simplicity).

While Group Y was working on Assignment A, Group X was also working on a similar assignment but for another engineering problem. Therefore, Group X is considered knowledge givers but on a different topic. Subsequently, both student groups transferred knowledge bi-directionally before starting the phase of Assignment B. This ensures that the KE cycle is completed, and each student gains the experience of being both knowledge giver and recipient.

2.3 Assessment Metrics

(Jer Yuen et al., 2007) conducted a survey on undergraduate students to find out their knowledge sharing habits. They found that students normally have a positive attitude towards knowledge sharing and were appreciative of its importance in peer learning. However, they are less inclined to sharing knowledge when it involved graded work for competition-related reasons. (Ong et al., 2011) conducted a similar survey and concluded that the motivation to share knowledge appears to be affected by relationships, rewards and the level of satisfaction with the knowledge sharing activities. (Brouwer et al., 2019) investigated various determinants of knowledge sharing and their effects on student success. Human nature makes altruism seldom a factor that encourages knowledge sharing. If no reward is present, a person who willingly shares knowledge do so knowing that this will lead to enhanced reputation as a personal benefit.

As rewards are a catalyst for positive attitude towards KS (Brouwer et al., 2019; Ong et al., 2011; Wolfe et al., 2008), we employ a two-fold reward system, where each student's final mark is the product of their group work mark and their individual contribution. First, all group members will share the same group mark based on the overall quality of their submitted work. This incentivises teamwork where everyone feels motivated to contribute with the aim of securing a good group mark in a healthy inter-group competition.

Second, a peer review exercise is adopted. Although we defined knowledge sharing among group members as a multi-directional process where all members are both knowledge givers and knowledge recipients; however, in practice, there are members who are passive, breaking the multi-directional links within the group. We attempted to identify proactive and passive members by making it compulsory for the students to complete a peer review form to assess the relative contribution of each member, ensuring that contributing members are rewarded appropriately, and 'free-riding' passive members are penalised. The exercise also fosters trust among members, which was proven as a precursor to catalysing KS and KT (Xue et al., 2011). Students share knowledge with group members because they feel their peers will be honest when assessing each other's contribution. This exercise can be viewed equivalent to the performance appraisal often adopted in companies which is one of the most effective ways to promote KS (Ling et al., 2009).

Metrics to evaluate the success of KE activities in the teaching and learning pipeline which involves researchers and academics are well covered in the literature. However, similar metrics for KE among tertiary students are missed out with little attention. It is easy to design quantitative metrics which suit different group work and/or KE approaches, as these are typically marks attained by students or class performance statistics. However, determining meaningful qualitative metrics remains a challenge because of the myriad intangible variables involved (*Royal Academy of Engineering: KEF Metrics*, 2018). Figure 2 presents the quantitative, qualitative and hybrid metrics used in the proposed framework. For the qualitative analysis, we leverage on AI-empowered qualitative metrics that uses dimensionality reduction to model the learning process as a grey box and provide human-interpretable visualisations.

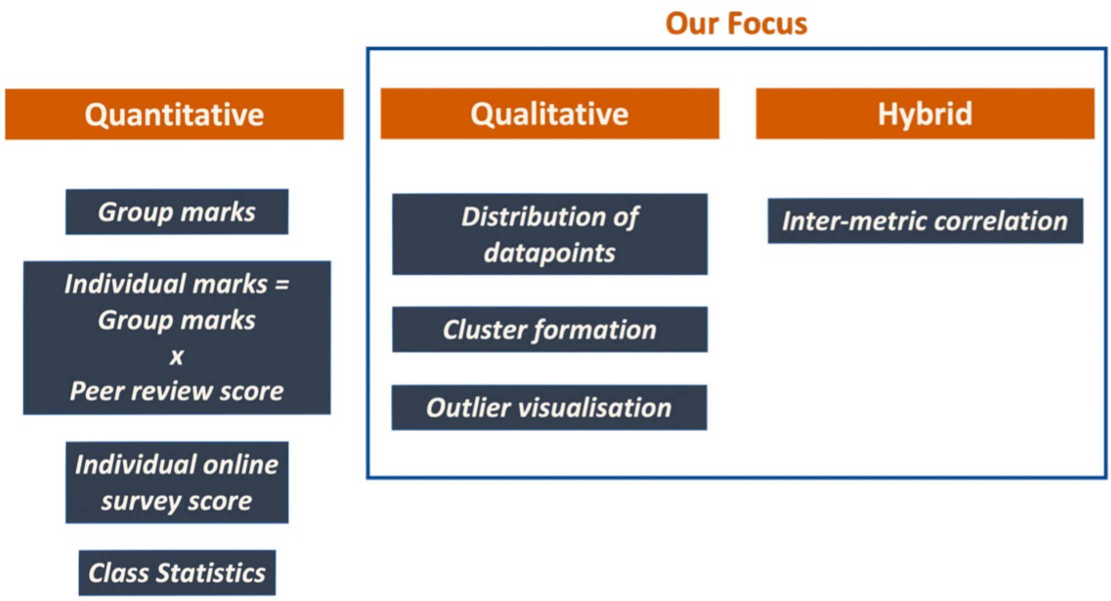


Figure 2: An Overview of the Evaluation Metric Categories in the Proposed KE Framework.

3. Visualisation of the KE Process

The evaluation of KE is an intricate, multi-variable process which is often difficult to gauge. Our work takes the process from hand-crafted methods to using AI-based dimensionality reduction which captures high-dimensional data and representing it in a low-dimensional map. The well-known *t-distributed stochastic neighbourhood embedding* (t-SNE) (Van Der Maaten et al., 2008) demonstrated significant success at producing 2D/3D visualisation of high-dimensional datasets. t-SNE was employed in several domains, such as speaker identification (Elnaggar et al., 2019), handwritten digits and images (Abdelmoula et al., 2016) and animal behaviour mapping (Todd et al., 2017). Its main function is to capture the local data structures, while retaining the global data distribution. Although explaining how t-SNE works is not the main scope of this paper, we simplify how t-SNE measures the similarity between input datapoints to construct the low-dimensional embedding. Its algorithm relies on transforming the Euclidean distances between pairs of datapoints $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$ (Equation 1) in the high-dimensional space (hyperspace) to a joint probability distribution $p_{j|i}$ that is the conditional probability of $\boldsymbol{x_j}$ having $\boldsymbol{x_i}$ as its neighbour in the low-dimensional map.

$$p_{j|i} = \frac{exp\left(-\|\boldsymbol{x_i} - \boldsymbol{x_j}\|^2 / 2\boldsymbol{\sigma_i}^2\right)}{\sum_{k \neq i} exp\left(-\|\boldsymbol{x_i} - \boldsymbol{x_k}\|^2 / 2\boldsymbol{\sigma_i}^2\right)} \quad , i \in \{1, 2, \dots, N\} \tag{1}$$

where $\boldsymbol{\sigma_i}$ is a parameter that is dependent on the local density in the high-dimensional space and N is the number of datapoints. As illustrated in Figure 3, the Euclidean distances between input datapoints are transformed into piecewise probabilities that act as attractive or repulsive forces between the output datapoints, $\boldsymbol{Y} = \{\boldsymbol{y_1}, \dots, \boldsymbol{y_N}\}$, in the low-dimensional space.

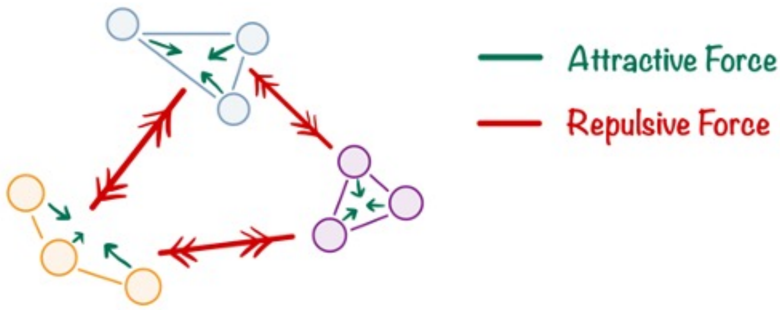


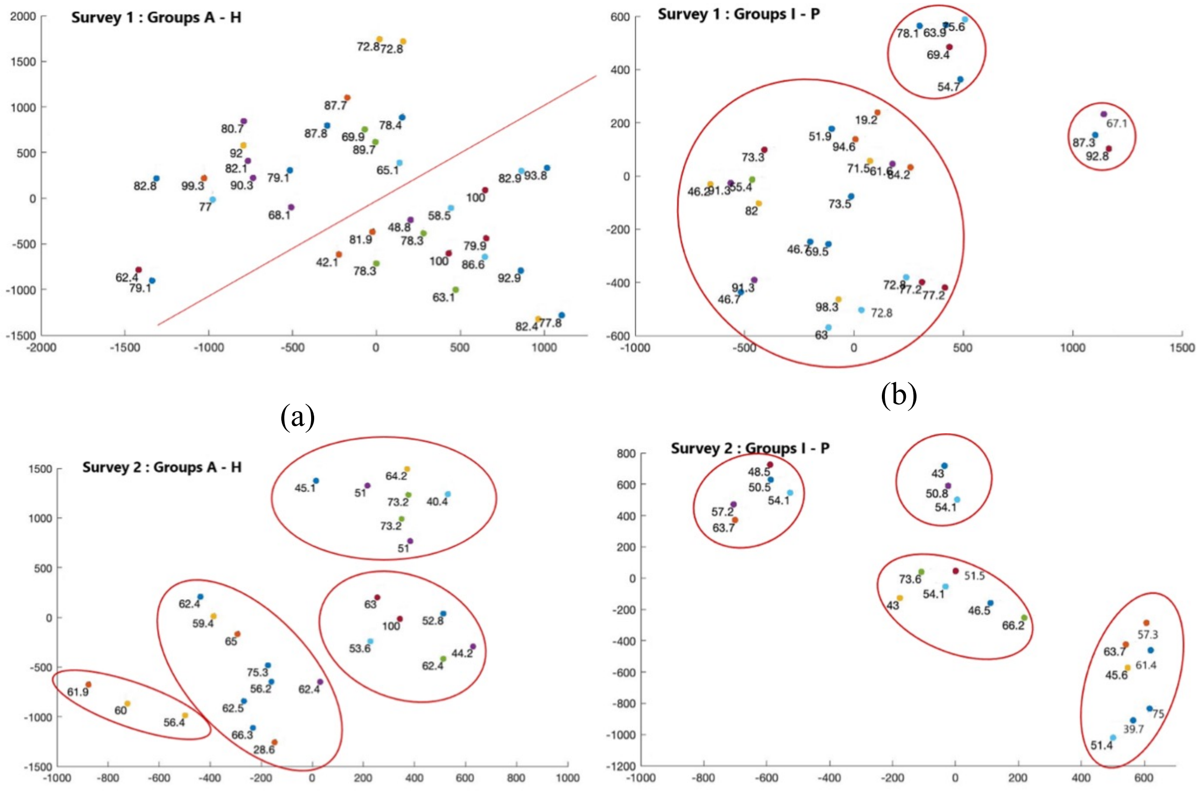
Figure 3: Datapoints Form Clusters of Similar Features in the Low-Dimensional Space

Speaking of datapoints, they represent the individual students who completed the online survey form. Each student's datapoint is constructed of eight different numerical and binary features based on their survey answers. The dimensionality reduction step should reproduce the student responses on a 2D map for visualisation. Therefore, t-SNE is responsible for transforming the 8D hyperspace to a 2D map.

4. Results and Discussion

The low-dimensional maps representing the survey-based student performance produced by t-SNE are shown in Figure 4. Datapoints of the same colour represent students from the same group. Additionally, some manually identified structures were drawn on the plots, showcasing how the proposed AI evaluation tool will help academics extract insights that were difficult to observe previously. Herein below we illustrate some of these insights.

Figures 4(a) and 4(b) show the results from the first survey (before the KT process takes place) for two student populations; Groups A-H and I-P who started with Assignments A and B respectively. Figures 4(c) and 4(d) show the results from the second survey (after the KT process took place). Individual marks are tagged to each datapoint. These are not true marks; they are scaled marks that reflect the statistics of the true marks for confidentiality reasons.



(c) (d)

Figure 4: 2D Maps of Student Performance Based on the Survey Responses from the Two Student Populations: Groups A-H (‘A’ And ‘C’) and Groups I-P (‘B’ And ‘D’).

4.1 Quantitative Metrics

Conventional group mark analysis reveals that all three groups, which achieved below 61% in Assignment A, ended with improved marks (as high as 16% increase) in Assignment B when provided with seed reports from other groups that scored marks above 70%. This practically demonstrates the boost in performance that the proposed KE framework brings to students.

4.2 Qualitative Metrics

4.2.1 Distribution of Datapoints and Cluster Formation

Comparing Figures 4(a) and 4(c) on the left for Groups A-H, it is evident that prior to the KT process, the *distribution of datapoints* is somehow random with no clear data structures. Since students at this stage have not studied the presented topic before, it was an expected outcome that most students will have similar shallow level of understanding. After the KT process, *data clusters* emerged indicating that student groups have shared a common pool of knowledge.

Similar observations apply to Groups I-P in Figures 4(b) and 4(d) respectively. Although the responses from the first survey yielded three clusters in Figure 4(b), the post-KT survey reveals far sparser clusters of datapoints as shown in Figure 4(d). The emergence of clusters in the second survey could stem from a number of reasons which include, but not limited to, the distribution of individual tasks among group members from different student groups. For instance, students from different groups who were responsible for literature search could share very similar pools of knowledge despite working from different groups. Therefore, AI-extracted insights like this fit to be extensions for future research.

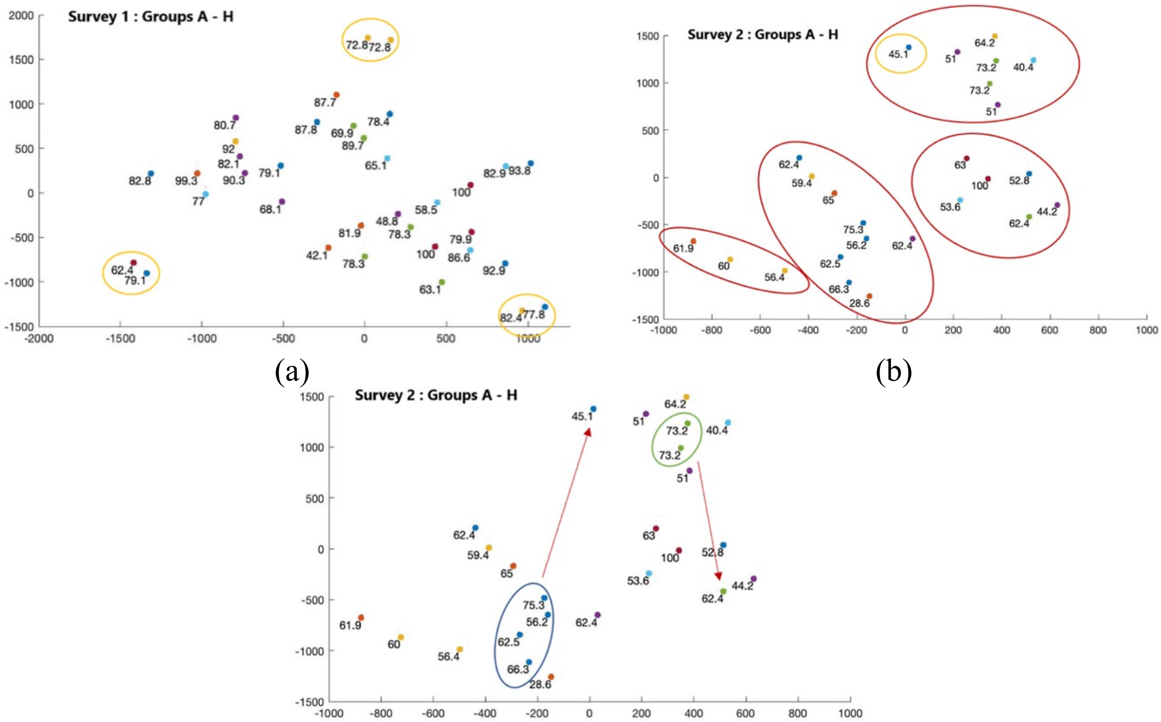
4.2.2 Outlier Visualisation

Outlier students are regarded as students who are spatially situated away from their peers in the low-dimensional maps. The presence of outliers does not necessarily indicate any positive or negative observations; it most importantly means that something interesting made those students stand out from the rest. The *datapoint outlier* phenomenon can be observed in Figures 5(a-b) which show 2D maps of student performance for Groups A-H. Before the KT process, there were six outlier students circled in yellow in Figure 5(a). A further work would be to study the reasons for such anomalies. After the KT process, there are no distinct outliers except for one mild case circled in yellow in Figure 5(b). This is expected since the KE process grew the students' understanding of the topic to comparable levels, explaining the sharp drop in the number of observed outliers.

4.3 Hybrid analysis

In contrast to the purely quantitative/qualitative approach covered in Sections 4.1 and 4.2, herein we present a hybrid analysis unveiling interesting inter-correlations. Two example student groups are highlighted in Figure 5(c). The blue circle contains four students forming a tight cluster with individual assignment marks between 56.2% and 75.3%. Recalling the outlier qualitative metric, it is clearly seen that a fifth poorly performing student (45.1%) is located far from their group cluster. This demonstrates the ability of t-SNE to differentiate students by the set of knowledge/skills they have acquired and their individual contribution. For this student, the knowledge or skills gained has set them apart from other members in terms of the mark attained which is much lower than the rest. Magnificently, t-SNE was able to identify such a difference from the students' survey-based input features independent from their awarded assignment marks. The same observation holds for the group circled in green.

The pure and hybrid analyses showcase t-SNE success in a new domain that is survey data. From an academic perspective, t-SNE qualifies to be a strong candidate for a complementary tool for academics to verify their formal assessment outcomes. Besides, leveraging on the inter-correlations between pure and hybrid metrics, lecturers can find new ways of verifying/resolving mark disputes by students. For instance, the case when a student raises a complaint about their peer assessment score for a group work.



(c)

Figure 5: Outlier Datapoint Visualisation (A-B) and Its Correlation with the Tagged Individual Student Marks (C).

5. Conclusion

The proposed framework brings the KE culture to HEI classrooms after it was exclusive to research and external collaborations. A bi-directional KE framework allows for intra- and inter-group KT enhancing the flow of knowledge throughout the student population and allowing students to reach similar levels of competence. From an employability perspective, the framework equips students with the skills needed to handle externally sourced knowledge and build upon it, making them more agile in their future dynamic workplaces. In contrast to the pure quantitative approach widely adopted in academic assessments, this paper leverages on t-SNE to produce AI-empowered visualisations based on survey responses and independent from individual student marks. Several interesting links between the quantitative and the proposed qualitative metrics were identified, enabling academics to verify formal assessment outcomes and/or resolve any marking-related disputes. Since the quality of t-SNE visualisations are heavily dependent on the survey-based data, the authors intend to further research ways of optimising the online survey questions to suit other engineering and non-engineering modules. The main aim of such a survey to provide an equal opportunity to each student demonstrating their knowledge and contribution independently from their role/task in their group.

References

Abdelmoula, W. M., Balluff, B., Englert, S., Dijkstra, J., Reinders, M. J. T., & Walch, A. (2016). *Data-driven identification of prognostic tumor subpopulations using spatially mapped t-SNE of mass spectrometry imaging data*. https://doi.org/10.1073/pnas.1510227113/-/DCSupplemental.www.pnas.org/cgi/doi/10.1073/pnas.1510227113

Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes*, *82*(1), 150–169. https://doi.org/10.1006/obhd.2000.2893

Asrar-ul-Haq, M., & Anwar, S. (2016). A systematic review of knowledge management and knowledge sharing: Trends, issues, and challenges. *Cogent Business and Management*, *3*(1), 1–17. https://doi.org/10.1080/23311975.2015.1127744

Boud, D., Cohen, R., & Sampson, J. (2014). Peer learning in higher education: Learning from and with each other. In *Education*. https://doi.org/10.4324/9781315042565

Boytsov, A., Fouquet, F., Hartmann, T., & LeTraon, Y. (2017). *Visualizing and Exploring Dynamic High-Dimensional Datasets with LION-tSNE*. 1–44. http://arxiv.org/abs/1708.04983

Brouwer, J., & Jansen, E. (2019). Beyond grades : developing knowledge sharing in learning communities as a graduate attribute. *Higher Education Research & Development*, *38*(2), 219–234. https://doi.org/10.1080/07294360.2018.1522619

Choo, C W and Alvarenga, R. (2010). Beyond the ba : managing enabling contexts in knowledge organizations. *Journal of Knowledge Management*, *14*(4), 592–610. https://doi.org/10.1108/13673271011059545

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Elnaggar, O., & Arelhi, R. (2019). A New Unsupervised Short-Utterance based Speaker Identification Approach with Parametric t-SNE Dimensionality Reduction. *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, *January*, 92–101. https://doi.org/10.1109/ICAIIC.2019.8669051

Jer Yuen, T., & Majid, M. S. (2007). Knowledge-sharing patterns of undergraduate students in Singapore. *Library Review*, *56*(6). https://doi.org/10.1108/00242530710760382

Joia, L. A., & Lemos, B. (2010). Relevant factors for tacit knowledge transfer within organisations. *Journal of Knowledge Management*, *14*(3), 410–427. https://doi.org/10.1108/13673271011050139

Ling, C. W., Sandhu, M. S., & Jain, K. K. (2009). Knowledge sharing in an American multinational company based in Malaysia. *Journal of Workplace Learning*, *21*(2), 125–142. https://doi.org/10.1108/13665620910934825

Ong, H. B., Yeap, P. F., Tan, S. H., & Chong, L. L. (2011). Factors Influencing Knowledge Sharing among Undergraduate Students: A Malaysian Perspective. *Industry and Higher Education*, *25*(2), 133–140. https://doi.org/10.5367/ihe.2011.0035

Royal Academy of Engineering: KEF Metrics. (2018). *https://www.raeng.org.uk/publications/responses/kef-metrics*, [Accessed: 17 August 2021].

Todd, J. G., Kain, J. S., & De Bivort, B. L. (2017). Systematic exploration of unsupervised methods for mapping behavior. *Physical Biology*, *14*(1). https://doi.org/10.1088/1478-3975/14/1/015002

Van Der Maaten, L. J. P., & Hinton, G. E. (2008). Visualizing high-dimensional data using t-sne. *Journal of Machine Learning Research*, *9*, 2579–2605. https://doi.org/10.1007/s10479-011-0841-3

Wei, C. C., Choy, C. S., Chew, G. G., & Yen, Y. Y. (2012). Knowledge sharing patterns of undergraduate students. *Library Review*, *61*(5), 327–344. https://doi.org/10.1108/00242531211280469

Wolfe, C., & Loraas, T. (2008). Knowledge Sharing: The Effects of Incentives, Environment, and Person. *Journal of Information Systems*, *22*(2), 53–76. https://doi.org/10.2308/jis.2008.22.2.53

Xue, Y., Bradley, J., & Liang, H. (2011). Team climate, empowering leadership, and knowledge sharing. *Journal of Knowledge Management*, *15*(2), 299–312. https://doi.org/10.1108/13673271111119709

Contact email: Omar.Elnaggar@liverpool.ac.uk