Data Analytic Framework on Student Participation in Generic Competence Development Activities

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***Abstract*—Generic competence is an important element in the development of students in tertiary education. Many scholars have emphasised the strong correlation between generic competence and engagement in co-curricular and extra-curricular activities. However, in the context of higher education, research into the frameworks of learning support platforms providing evidence-based support for students' whole-person development is very limited. This study aims to investigate the potential of applying data analytics to learning support platforms with the purpose of developing students' generic competence in higher education. Recognising the potential of the latest advances in data analytics technology, the 'Student Activities Intelligent Learning Support' (SAILS) platform is proposed. To investigate its applicability and user acceptance, a prototype will be implemented and tested in a self-financing institution in Hong Kong. The users, including students and academic professionals, will be given suggestions regarding a student's involvement in various student activities with consideration of the past learning experiences, the personal developmental needs and the stated learning outcomes of the institution. The framework will benefit students as well as academics and institutions. Students, especially freshmen, can further enhance their generic competence by selecting suitable activities.**

Keywords—Learning management system, data analytics, generic competences, AI assisted personal development, machine learning

I. Introduction

Generic competence (GC) is a critical element in the development of students in tertiary education, in addition to discipline-oriented learning. Numerous studies have conducted on students' GC, delving into issues such as its definition [1], evaluation [2], relation to learning in the discipline [3] and impact on academic results in the formal curriculum [4].

Many scholars, educators and student activities developers have devoted significant efforts to various dimensions of generic skills, considering them with respect to measurable outcomes and as a basis for defining educational strategies. Such efforts have included defining and assessing generic skills [1], developing generic skills [5], understanding the relationships between generic skills and discipline-specific factors and identifying other determinants of generic competencies [3, 6, 7], as well as impact of extracurricular activities participation of students' academic performance [8]. In Trowler's study [9], the significance of the effort and resource put by the students and the institutions is considered as the driving forces to enhance the overall learning experiences for the benefits of students and the institutions' reputation. Kuh [10] stated that to assess the quality of tertiary education, accurate information is needed to fully understand student engagement, especially because it describes the time and energy students devote to educationally sound activities both inside and outside the classroom and the institutional policies and practices in place to motivate student participation in activities.

Unlike curricular activities that are regarded as a part of formal curriculum, co-curricular activities are those outside of but complementing the formal curriculum and the extra-curricular activities are those not tied to the curriculum [11]. Co-curricular activities and extra-curricular activities are key components in GC development. Co-curricular activities are closely related to the discipline and are sometimes embedded into program design, whilst extra-curricular activities help to develop the basic skills and general knowledge that everyone needs.

Participation in student activities, both co-curricular and extra-curricular, is usually voluntary. Broadly speaking, learning by participation in extra-curricular activities is a form of self-regulated learning in that students are expected to self-control and self-evaluate [12-13]. Hence, students have the freedom to choose among activities and to use their own judgement in setting the pace of their learning progress.

II. Intelligence in Learning Support Platforms

Learning management systems (LMS) give the platform to provide the learning contents and allow students to interact with the teaching institutions to accomplish a wide range of process in learning and teaching [14]. Such a system is critical in the current education environment. Systems such as Canvas, Moodle and Blackboard are widely used in higher education (HE) to support administration, content management and interactive teaching.

Smart Learning Environments (SLE) can be regarded as the learning environments supported by technology to adapt the individual learner's need and give corresponding timely support [15]. Data analytics (DA) is a critical enabling technology in SLE and plays a significant role supporting intelligence in learning. DA, generally speaking, is a process in which data sets are used to draw conclusions about the information and to discover new relationships and new data [16-17]. DA is widely used in various commercial and non-commercial applications to assist in making informed decisions. Learning analytics (LA) and education data mining (EDM) have been developed and widely implemented in education, and whilst the former focuses upon the entire education environment and upon interaction between instructors and learners, and the latter is often used for automated adaptation [18]. Definitions of LA vary across research areas, but it is generally accepted that LA uses student-generated data and their context for understanding and optimising learning with a focus on the four criteria for learning analytics: whether they support learning, whether they support teaching, whether they are widely deployed and whether their use is ethical [19].

Education is not one size fits all, so the learning analytics is expected to circumvent the homogenized learning environment, at least should not worsen it [20]. SLE should facilitate personalised learning experience leveraging the advancement of enabling technology, and intelligence can be injected to it to realize personalised adaptation. Some conceptual frameworks are suggested. The smart pedagogy framework [21] is based on recent technological advances that enhance the wider educational environment. Adaptive education systems also address learning needs at the individual level in the content provision by analysing individual's personality traits and skills and catering the personal needs [22].

III. Research Gap

Fig 1 illustrates the currently available products and platforms related to the adaptability of LMS along with the learning scopes. Regarding learning scopes, many LMS are available on the market, such as Canvas, Moodle and Blackboard, that support discipline-based academic subjects and are widely used and well developed. Therefore, recent efforts in this field have focused on the use of SLE and related technologies to personalise learning. In their current support of student activities, institutions are using various student management systems to document student engagement for administrative purposes.

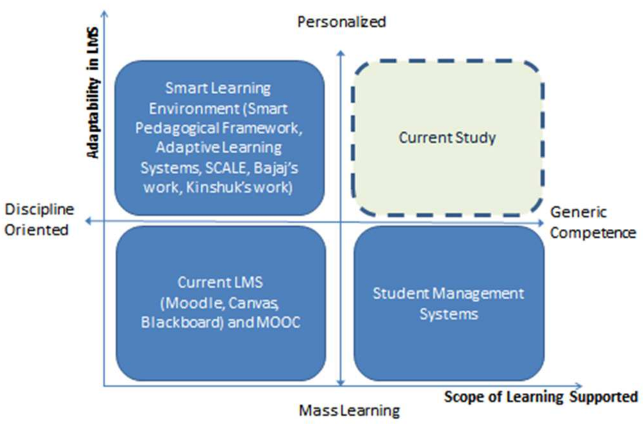

Fig. 1 Adaptability in Student LMS and the Scope of Supported Learning

In formal academic systems, the pattern of the studies is well structured. The requirements of credits and course distributions are usually clear to students, instructors and administrators. However, the inclusion of student activities in GC development is quite different. Such activities are neither credit-bearing nor required for graduation in most cases, so there is less clarity about how students get involved in various student activities and thus enhance GC development. To improve personalisation, considerable research interest has been directed towards the creation of an LMS that includes more intelligence and DA technology. Context-awareness is a key feature of SLE, but context may involve manifold aspects [23], and current efforts have not yet effectively addressed this issue in terms of developing GC.

Support for students in HE as they plan their campus life and GC development remains insufficient and lacks structure. Students, especially freshmen without experience in tertiary education, choose the nature and degree of their involvement in student activities, but the choices often quite arbitrary and influenced by their peers. Many students do not know how to plan their college life purposefully and effectively to help realise the aspirations they have for their careers and personal life. Even the professional academic staff/advisors who provide consultations need finer-grained information about the students and other objective criteria to support their planning. However, research into methods to provide an evidence-based systematic framework that supports GC development in educational settings has been limited.

The model should also incorporate the identification of the competence needed for the students to be successful in their professions. Some prevailing tools can be used to investigate the gaps of the student competences and the desired characteristics of their career aspiration.

Therefore, this study will focus on developing an extended model on students' holistic development through SLEs and addressing the following research questions:

- "What are the insights can be learned from the learning analytics on the students to identify their learning needs and pattern on activity engagement?"
- "What is the relationship between the choice of learning activities and student background?"
- "Can progress in data analytics and machine learning contribute to a new approach to provide personalised, systematic and evidence-based information that promotes students' holistic development?' and
- "How can students become sufficiently well informed and advised so that their decisions regarding campus activities match their career aspirations, their own competences and the institution's expectations?"

IV. Framework to Match Student Needs and Learning Opportunities

This study will investigate the framework needed to evaluate the practicality of DA in GC. This effort will integrate the data of students' profiles, institutional information and the records of graduates and previous cohorts into a DA system. This framework will help students to choose among activities that contribute to their GC development, based on their GC expectations, career aspirations, personal experience and the experiences of previous students.

With reference to the Smart Competence Analytics in the LEarning (SCALE) model [23], we proposed a framework that will be implemented with layers of sensing, analysis, competence and visualisation. This framework is called Student Activities Intelligent Learning Support' (SAILS) and it is a three-tier model, as shown in Fig 2, complete with data sources, intelligent systems and the user interface.

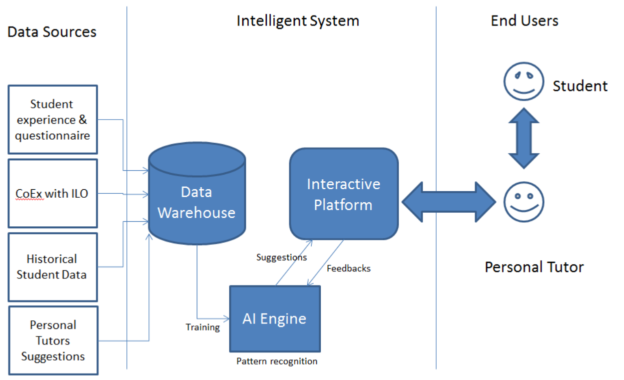

Fig. 2 Student Activities Intelligent Learning Support (SAILS) Framework

Therefore, the objectives of the study are:

- To investigate the applicability of various personality tests or tools to address the needs in the development of generic competence with reference to their academic programs.
- To identify the pattern of students' involvement in student development activities with their personality by applying data analytics and pattern recognition.
- To investigate how the students' involvement in student development activities is correlating with the changes in academic performance and their generic competences in associate degree students.
- To develop an extended model in developing students' holistic development by enhancing the existing model.

Data source: This will contain the students' profile and details about the activities provided. The students' profiles are critical to the success of intelligent systems that address individual students' needs in a learning context [24]. Data will include students' needs, their current and expected level of GC, their personal aspirations, their past learning experiences and information about the activities provided and their intended learning outcomes. After the data are collected, they will be cleaned, reconciled and stored in the data warehouse.

Intelligence System (AI Engine): The aim of the data analytics will be to identify gaps among individual learning profiles, current competences, career aspirations and the institution's expectations of their graduates by gathering and processing relevant data. These similarities and differences are represented by 'distance' using data clustering techniques such as K-means. These results come from machine-learning engines and other sources and serve in the analysis of students' needs and personal situations.

Interactive Platform: This interacts with the users in an adaptive manner to produce personalised suggestions and results pertaining to personal development activities. The responses from the students and their personal tutors will also be the source of the data used to train the machine-learning engine.

V. Evaluation Model

Inspired by the model proposed by Wong, Wong and Yeung [25], we plan to evaluate the usefulness of SAILS along with the degree of its acceptance by users, including advisors and students. The following outlines the general evaluation framework. Their model is a combination of Davis' [26] technology acceptance model (TAM) and its extended versions as provided by Park, Nam and Cha [27] and Venkatesh and Davis [28]. Wong, Wong and Yeung [25] considered those constructs in TAM and in the extended models that are most relevant to the students' acceptance of response system technologies. The model used by Wong, Wong and Yeung [25] is particularly applicable to this evaluation of the students' acceptance of SAILS and is illustrated in Fig 3.

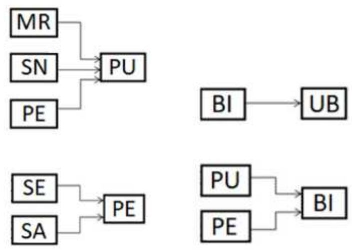

Fig. 3 Extended Technology Acceptance Model for Evaluating the Framework

In our evaluation, we aim to investigate the extent to which users like the platform provided by the framework. Their responses will be viewed in light of usage behaviour (UB), to use Davis's term, which is the indicator of the user's acceptance of the proposed SAILS framework. UB is determined by users' intentions, that is, by how the students and advisors approach the use of SAILS, reflecting a phenomenon known as behaviour intention (BI). Furthermore, BI has been attributed to both perceived usefulness (PU), which in is the user's perception that SAILS is useful for choosing among activities, and to the perceived ease of use (PE), which is the user's perception that SAILS is user-friendly. PU is also affected by the relevance and the behaviour of other users. Relevance, which is defined as relevance to a major (MR) in Park's term, reflects the users' perception of both the information and suggestions' relevance to their personal needs and aspirations. The factor of others' usage behaviours, which is termed the subjective norm (SN), is the influence of their peers on an individual user due to the 'herding effect'. PE also has a direct influence on perceived usefulness. However, PE reflects the users' perception of the degree of ease in the use of SAILS in the given context, beginning with data input and ending with the resulting suggestions. PE is influenced by self-efficacy (SE) and self-accessibility (SA), in which SE reflects the student's perception that users already have the skills to use SAILS, and SA simply reflects their right to access these systems.

The questionnaires will be developed to measure MR, SN, SE, SA, PU and BI to better understand the user's perspective, and UB can be indicated by usage behaviours.

VI. Research Plan and Methodology

With the previous studies in reviewing current research on and advances in the Education Technology (EduTech) that incorporate different intelligence by AI and machine learning, we also investigate their suitability and feasibility in facilitating student learning in GC and specifically to promote whole-person development.

A. Identifying students' personalised needs

We attempt to understand the extent of the matching of the students' choice on the academic program based on their self-understanding and previous academic background.

To identify the students' personalised needs in the development of generic competence with reference to their academic programs, some well-developed personality evaluation tools are deployed. The gap of areas of GC development is identified. We study the difference of the expected desire of the academic discipline and personal attributes in RIASEC model.

Holland [29] developed a model to facilitate an individual's choice of vocational direction, not only according to their skills and abilities but also according to their attitudes and values. According to Holland, individuals can be characterised by their degree of resemblance to each of the six personality types: Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E) and Conventional (C). Holland's theory has been widely adopted in career advising [30-31], and this personality test has become a resource in student guidance [32].

To investigate the applicability of the Holland's Code in identifying the personalised need in GC given their choices in academic programs.

B. Pattern Recognition for Student Activity Involvement

DA will be applied to the data to reveal patterns of student involvement in various student activities, especially those oriented towards GC improvement and academic achievement.

To use data analytics and pattern recognition to identify patterns of student involvement. It will discover whether the students tend on choosing the activities that are enhancing the GCs that they are already good at, that they need to improve, or that the academic program's needs.

Data mining techniques, including K-means and Bayesian methods, will detect clusters, group data and carry out association rule learning to discover the relationships among the variables in the data sets.

C. Impact on the students' involvement in GC

The project also studies the impact on the students' involvement in GC development activities on the academic results. The subjects to be gathered will be associate degree students.

There are studies on the impact on the extent of involvement in extra-curricular activities on the academic results leading to three streams of the thoughts [4]: Development model (the more involvement the better), Zero-sum model (the less involvement the better), and threshold model (good to involve in some extent, but bad after some threshold).

Knowing the most students in associate degree students in Hong Kong aims for further studies, which model is suitable to them? It will be useful in designing the study plan on GC development and suggesting GC activities for the students.

D. Developing framework for students' holistic development

The required framework gathers and manipulates data on both an individual basis and an institutional level. On an individual basis, students' profiles are built up to include learning experiences in high school, career aspirations and current competence levels in various dimensions (collected from the self-assessment questionnaire about GC). At the institutional level, the institution's expectations of their graduates' attributes, the details of their student activities, to include each of their intended learning outcomes (ILOs), which reflect the expected learning after a learning activity, and the experiences of graduates in previous cohorts.

Next, the detail of this framework will be developed as the blueprint for the platform's development and it will incorporate the students' responses and career aspirations, with information and advice provided in SAILS. This step refines the framework described above and is illustrated in Fig 2. A framework will be designed to analyse the nature and degree of student involvement in various activities oriented towards various ILOs. This will contain the student data, the activity's attributes and intended learning outcomes and the previous suggestions of personal tutors. Therefore, a profile is constructed for each student to allow for the accurate identification of gaps between their actual learning experience and their expected learning outcomes.

The data sources include learning experiences in high schools, career aspirations, current competence level, information of student activities, the experiences of graduates in previous cohorts.

The data sources are the following:

- Learning experiences in high schools – This refers to Other Learning Experience and the extra-curricular experiences in their secondary schools.
- Student career aspirations – A questionnaire derived from Holland's code in RIASEC theory will be distributed to students in their first semester of study.
- Current competence levels in various dimensions – A self-assessment questionnaire on GC will also be distributed to students.
- Details of all student activities with intended learning outcomes (ILOs).
- Institution's expectations of graduate attributes – In this study, a tertiary education institution enrolling over 4,000 new students every year is used as the case study.
- The experiences of graduates in previous cohorts – learning experiences and participation in student activities will be retrieved.

The acquired data will be cleaned, reconciled and integrated into the data warehouse under a united schema.

E. Prototype Platform Development

A prototype platform will be deployed in the self-financed arm of a university in Hong Kong having over 8,000 students. A set of historic data will be used to train the platform with machine-learning technology in pattern recognition, and the data will include the cases of successful alumni from the perspective of both academic achievement and generic competence.

The platform is built using a model that facilitates iterative cycles, such as the widely used action-design-research (ADR) model [34]. In its development, an open-source tool for the collection, analysis, visualisation and interpretation of data, as offered by the machine-learning and visualization tools applied on the dataset.

To visualise the analysis and suggestion, an interface, such as a dashboard, will form a visualisation layer to allow users to view their results and interact with the settings for those results. The students will be given a list of recommended student activities and informed about their expected outcomes, taking into account the individual's learning experiences, GC and career aspirations. The platform will provide suggestions regarding the type and duration of activities according to the data and analytics (factoring in current students with certain similarities and previous students in similar situations).

The platform will allow students and advisors to choose their preferences along a spectrum that includes improving academic performance and enhancing GC. The platform will respond to their preferences and modify its advice accordingly.

F. *User Engagement and Feedback*

It is worth noting that during the developmental and testing stage of this study, the students will use the prototype platform alongside their personal tutor because the suitability of suggestion (usefulness), as well and the ease of use, are the principle areas to be investigated.

With the proposed SAILS platform, when a student meets their personal tutor for the first time, the platform draws on the student's profile and uses a machine-learning with a back-end intelligence engine to generate suggestions. The personal tutor will review the suggestions and either agree, disagree or partially agree before using the platform to provide the students with their own suggestions and opinions. The personal tutor and student will each respond independently to the suitability of the suggestions. The platform will evaluate the difference between the intelligent engine and the personal tutors. This data, combined with feedback from the students and their personal tutors, are fed into the platform for training.

A group of personal tutors will also provide suggestions to the students based on their profiles. For each case, the personal tutor will score the platform's suggestions according to a set of attributes that include appropriateness, creativity and timeliness. They will be evaluated by considering the difference between the student's actual choices and the suggestions from other sources. The gaps and the similarities will also be used as a source of data to be fed to the platform for training.

VII. Evaluation of the Framework

At the end of the semester, a study will be conducted of the personal tutors and students to review their acceptance of the platform and their evaluations of its effectiveness with reference to a set of attributes that are part of the above mentioned TAM model. In particular, this step will evaluate the extent to which the platform is perceived as providing students with sensible suggestions and useful information.

A set of the questionnaire will be designed to investigate user acceptance in the context of research and given to both freshmen and to others who have used to the platform. The platform's acceptance and its effectiveness are evaluated with a questionnaire and in focus groups that include both users and non-users among a group of stakeholders, including students, personal tutors and professional counsellors.

Furthermore, the extent to which the students will consider and ultimately follow the platform's suggestions is another concern. Students may end up enrolling in the suggested activities, in those that were not suggested, or in those that had similar activities of the same type (with the same ILOs) or in other activities, it might also be possible that some students decide to not participate in any activity. This information is important for evaluating the students' acceptance of the platform. With this data, the platform will be enhanced in terms of its ability to match student profiles with ILOs. It is worth noting that this project will use ILOs as features to facilitate matching of activities. Whether or not the learning activities can attain ILOs is out of the scope. A questionnaire will also be given to final-year students to track their changes in attitude regarding their GC.

VIII. Conclusion

SAILS users will be given suggestions regarding their involvement in various student activities and their personal development with consideration of their personal aspirations and the institution's stated goals.

It also uses the records of behaviours of graduates and previous cohorts as references. This systematic approach to student advising shows much promise in the area of GC for students and other stakeholders. A more well-informed and tailor-made plan of activities will be generated by data analytics and intelligent systems to reflect their personal aspirations and past learning experiences.

SAILS will allow visualisation of information about students' GC needs, thus becoming a resource that institutions can use to sponsor student activities with an eye on students' whole-person development. This system also allows visualisation of students' progress in fulfilling the Intended Learning Outcomes (ILOs), which is useful for the development of future GC activities and strategies.

Acknowledgment

This study was supported by the Faculty Development Scheme (No. UGC/FDS24/E09/20) of the University Grant Committee of Hong Kong.

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