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Towards an Institutional Analytics Agenda for Addressing Student Dropouts in Higher Education: An Academic Stakeholders' Perspective

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Abstract

Although the number of students in Higher Education Institutions (HEIs) has increased over the past two decades, students gaining an academic degree is far from assured. To that end, Institutional Analytics (IA) can offer insights to support strategic planning with the aim to reduce dropouts and therefore to minimize their negative impact (e.g, on students, academic stakeholders, and institutions). However, it is not clear how institutional stakeholders can integrate IA in their practice to overcome academic-related issues and to offer support to students who struggle achieving their academic goals. To address this gap, we conducted focus groups with 13 institutional stakeholders of an Estonian university. By analysing the focus group data, we identified 3 main categories of factors influencing dropout from the perspective of institutional stakeholders: (1) institutional experience, (2) educational goals, and (3) personal aspects. We discuss our findings from an institutional perspective with the aim to reflect on institutional processes, organizational structures and facilitatory roles in the context of dropouts in Higher Education. We argue that IA can provide insights concerning students' institutional experience, educational goals and personal aspects to further support decision-making on the institutional level. We envision that our findings contribute towards a participatory agenda for the design, implementation and integration of IA solutions focusing on addressing dropouts in Higher Education.

Notes for Practice

- Dropouts in Higher Education is a worldwide societal problem, also with negative impact on Higher Education Institutions' (HEIs') reputation and function.
- Institutional Analytics is a promising approach for addressing dropout in Higher Education.
- In this article, we identify dropout reasons and map institutional analytics solutions that can inform HEIs strategic planning.
- Results suggest that focusing only on maximizing student performance does not help reduce dropouts. Beyond classic indicators based on student academic history or engagement, other factors such as curriculum, institutional and social support should be considered to predict student retention.
- To reduce dropout, HEIs can implement institutional analytics solutions such as student dropout prediction models, competence-based models, or intelligent recommender systems that propose interventions to support students' academic performance / overcome students academic struggles
- Institutional-wide mentoring programs, introductory courses, counseling, and curriculum improvements have a great potential in overcoming dropouts which have been identified through Institutional Analytics.
- While institutional analytics solutions are evidence-based, there is a need for contextualization. As such, we envision that a human should mediate the interpretation of the analysis before triggering any intervention.

Keywords

Institutional Analytics, Student Dropout, Student Success, Higher Education Institutions

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1. Introduction

In this work, we aim to synthesize the perspectives of researchers, and institutional stakeholders to understand, and address dropouts with the support of data. To do so, we systematically explored institutional stakeholders' perceptions towards Institutional Analytics (IA) as a means to reflect on and further support institutional processes, organizational structures and facilitatory roles in the context of dropouts in Higher Education (HE). We followed a participatory approach to gather insights by conducting a series of focus groups with institutional stakeholders'. We envision that our work contributes to offering insights and to supporting sense-making regarding the dropout interpretation and the decision-making processes on the institutional level based on analytics.

According to the Organisation for Economic Co-operation and Development (OECD) (Kaplan, James, Figueroa, Rawkins, & Dumont, 2020), the graduates from Higher Education Institutions (HEIs) enjoy tax and other benefits – such as faster economic growth and increased productivity – compared to non-holders of academic degrees (Brennan, Niccolo, Séné, & Tanguy, 2013). Still, many students drop out from HEIs despite the benefits mentioned above and to such an extent that dropouts pose a significant and costly challenge for HEIs globally (Wild & Heuling, 2020). According to Vossensteyn et al. (Vossensteyn et al., 2015), every third student who enrolls in a HE program will either move to another program or leave without finishing it (Ameri, Fard, Chinnam, & Reddy, 2016).

The completion rate of Bachelor's studies in OECD countries on average is 39% in three years and 67% in 3+3 years (Kaplan et al., 2020). In Estonia, the respective numbers are 34% and 59%, respectively (Kaplan et al., 2020). Thus, approximately 40% of HE students in Estonia never finish their studies. The OECD data also show that the share of students in Estonia who enrolled in bachelor studies and are no longer enrolled in tertiary education (and have not graduated) 3+3 years after the start is one of the highest - that is, 33% compared to OECD average of 24% (Kaplan et al., 2020). This shows that high dropout rates extend beyond the first year of studies despite the labour market's need for graduates (Brennan et al., 2013). Reducing dropouts in HE was one of the key strategies in Europe's 2020 plan (Vossensteyn et al., 2015) and a long-term goal for many HEIs (Wild & Heuling, 2020; Vossensteyn et al., 2015). To achieve this goal, it is necessary to identify the factors that may lead students to drop out (Tinto, 1975; Spady, 1970; Cabrera, Nora, & Castaneda, 1992). The early identification of risk factors enables academic (or else, institutional) stakeholders, such as program directors and student counsellors, to take action.

Institutional Analytics (IA) can be used to measure and analyze students' data (for example grades, and admission details) to gain insights for improving teaching, learning, and curriculum development. Related research explored the impact of factors, such as personal values, teaching quality, and satisfaction, on student dropouts in specific specializations (e.g., nursing and software-engineering) (Giannakos, Pappas, Jaccheri, & Sampson, 2017) or specific student groups (for example, students from disadvantaged backgrounds (Herbaut, 2020)) by analyzing quantitative data from online learning platforms (Fei & Yeung, 2015) and study information systems (I.-A. Chounta, Uiboleht, Roosimäe, Pedaste, & Valk, 2020). However, to the best of our knowledge, there is no widely-accepted framework or set of data-informed indicators for predicting dropouts in HE.

Related research focuses on dropout factors from the students' perspective (Chen, 2012). However, it is essential to engage other institutional stakeholders (for example teachers, and curriculum developers) in the discussion because they can influence academic policies and to take proactive measures for reducing dropouts by reinforcing improvements in teaching, changes in course contents and curriculum development, providing support services, and improving student experience (Arnold & Pistilli, 2012; Colvin et al., 2015). To implement successful strategies, a thorough understanding of the fundamental issues that affect student dropouts is necessary (Behr, Giese, & Theune, 2020). For that, we require data-driven IA to effectively identify students who may be at risk and to place appropriate policies for supporting these students. At the same time, there is a need for qualitative approaches to help us interpret and contextualize data-informed insights from the perspectives of institutional stakeholders (I. W. Li & Carroll, 2020). This combination can help us understand the needs of stakeholders and solidify the integration of IA solutions in practice.

This paper explores the perceptions of institutional stakeholders with respect to HE dropouts, factors influencing dropout and the role of the institution in reducing it with the help of IA. In the following section, we provide an overview of related work, leading us to the specific research questions tackled in this paper. Next, we present the methodological approach, demonstrate the results of the analysis and we provide a contextualized discussion based on the findings. Finally, we conclude with the limitations of this work and offer directions for future research.

2. Related Work

2.1 Dropout predictors

We define dropouts as the ”students’ ex-matriculation from the respective study program for reasons that indicate lack of interest, motivation, capability or willingness to pursue their academic degree” (I.-A. Chounta et al., 2020; Spady, 1970). A substantial body of literature examines factors that may lead to dropouts, and the models introduced by Tinto (1975), Spady (1970) and Cabrera et al. (1992) are some of the well-known models. In 1970, Spady introduced the student dropout model and its popularized by Tinto’s student integration model. Both studies identified different characteristics such as prior academic integration (student grades), institutional commitment, student goal commitment and social integration. Out of the identified factors, academic integration is highlighted as the most substantial predictor (Tinto, 1975; Spady, 1970). Cabrera et al. (1992) offer an model that yields a different understanding, where the emphasis has been placed on the psychological and sociological processes underlying dropout behaviour. Likewise, many studies focus on different dropout behaviour patterns.

According to Crosling et al. (Glenda, Heagney, & Thomas, 2009), dropouts can arise due to the quantity and quality of the pre-information students receive regarding the admission process, quality of the teaching, the way assessments have been designed, curriculum development. Bean (Bean, 1980) argued that the quality of the institution (as measured by course dissatisfaction, and facilities such as the quality of classrooms/library/campus environment/food service (Patti, 1993; Ullah, Alam, Mahiuddin, & Rahman, 2019)), and the staff-student relationship (as measured by students’ willingness to discuss learning tasks with academic staff, and the level of sensitivity and availability to individual student needs) are important factors when predicting dropouts.

From the social and personal perspective, (Hinton, 2007) argued that feelings of isolation, homesickness, accommodation and transportation issues, and especially workload-related issues might lead to dropouts (Bean, 1980). Bean et al. noted students’ background, socioeconomic factors, residency as some of the predictors (Bean, 1980). Social engagement during the university, personal characteristics (for example, gender and family background), financial difficulties, pr health issues are social factors that can influence the dropouts (Glenda et al., 2009; Willcoxson, Cotter, & Joy, 2011; I. W. Li & Carroll, 2020).

Concerning the educational background and the learning profile of the students, several empirical studies emphasise that university entrance scores and grades (Chen, 2012), prior academic performance (Johnson, 2008; Hoffman, Richmond, Morrow, & Salomone, 2002) and the lack of commitment to studies can impact dropouts, especially in the first year of studies (Willcoxson et al., 2011). According to Jaggo (2020), students who drop out during the first year of studies have lower state-exam grades compared to the students who continue their studies. Additional factors that may influence dropouts can be the students’ problem solving and cognitive skills (Finn et al., 2014), students’ motivation, persistence, loss of academic self-confidence, and locus of control (Xenosa, Pierrakeasa, & Pintelas, 2002; Seymour & Hewitt, 1997) as well as prior academic performance (I. Li & Dockery, 2015). Some studies have focused on students’ dissatisfaction towards specialisation/program, and dropout rates (Jung & Kim, 2018), cultural adjustments, language acquisition, and quality of the studies as potential risk factors (Jung & Kim, 2018).

Related work regarding dropouts focuses on social origin (Herbaut, 2020; Georg, 2009). For example, the students who come from less advantaged backgrounds have a higher tendency to drop out (Herbaut, 2020; Georg, 2009). Further, research suggests that students may drop out due to problems related to academic activities or voluntary withdrawal (such as personal issues, health issues) (Tinto, 1975; I. W. Li & Carroll, 2020). However, if institutions fail at distinguishing the core factors within their context, their strategies and policies may not have a significant impact on the student success (Tinto, 1975). Our work differentiates from existing research since we attempt to elicit those **contextual factors that affect dropouts in a HEI** to lead the design of an IA solution and **support the academic stakeholders to intervene when students are at risk**.

2.2 Potential impact of using Institutional Analytics to address dropouts

Related research has focused on data-informed methods - such as Learning Analytics (LA) - for assessing student dropouts at the HEI level. Nonetheless, there is still a lack of significant evidence on the link between LA and dropouts (Ifenthaler & Yau, 2020).

Data-informed approaches can support institutional stakeholders in monitoring the students’ progress, current status, and behaviours and potentially assessing the risks students may face. In this sense, LA can offer a potential solution for designing interventions to help students at risk. LA is the continuous and iterative process of collecting, evaluating, analysing and reporting institutional data to make decisions (Siemens & Long, 2011). LA can aim at different granularity levels such as the individual, classroom or institutional level. Here, we define as IA the application of LA methods at the institutional level (Romero & Ventura, 2020).

Research on LA solutions designed to predict students at risk includes Course Signals implemented at Purdue University (Arnold & Pistilli, 2012), Prediction models implemented at the University of Phoenix (Barber and Sharkey 2012) (Barber &

Sharkey, 2012), Mockup dashboard for individual students developed at the Open University UK (Wolff, Zdrahal, Herrmannova, Kuzilek, & Hlosta, 2014), and Student Success System developed at University of Wisconsin (Shehata & Arnold, 2015). Course Signals provided real-time feedback by traffic light signals (likelihood of success: Green-successful, Red-Fail, Yellow-potential problems) based on the student performance such as course grades, past academic history (GPA, test scores), demographic variables (age, attempted credits, and residency). However, researchers have brought out some criticisms in course signals. For example, Prude University has proved that the course signals can increase student retention. However, according to Caulfield's article, we can see that the retention rate has improved even without using course signals when looking at the data through the different years. So then the question is, what are the causes which have impacted this retention (Caulfield, 2013).

The University of Phoenix has used the data from Student Information Systems (SIS), Learning Management Systems (LMS), and financial aid systems to develop a prediction model to address dropouts. Follow-up cross-validation procedures verified that there is an 85-95 accuracy of predicting whether the students would pass or fail a course. Those results emphasised that predictive models of identifying students at-risk have higher accuracy. Sociocultural aspects may come into play when it comes to the adoption and effectiveness of the systems mentioned above (Arnold & Pistilli, 2012; Barber & Sharkey, 2012) – both systems were designed and implemented in a specific geographical and cultural context. Here, we reference these works as examples in related literature that focused on the potentials of LA for supporting study success and dropouts (Ifenthaler, 2015).

For the implementation, existing solutions typically employ descriptive and quantitative indicators, such as:

- *students' personal information*: gender, age, learning disability (if any), prior education history, discipline history (if any), (Daud et al., 2017; Mitra & Goldstein, 2015; Rogers, Colvin, & Chiera, 2014; Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018);
- *financial and professional status* : family income, family assets, work experience and current employment status (Rogers et al., 2014; Daud et al., 2017);
- *academic background*: admission scores, information regarding schools the student has attended in the past (level, type, name), enrolment options (the other specialisations or faculties that student has applied), enrollment year (Daud et al., 2017; Mitra & Goldstein, 2015; Rogers et al., 2014; Gkontzis et al., 2018));
- *student engagement with LMS and virtual learning environments*: numbers and patterns of login activity, time spent online, information regarding submissions assignments, activity on discussion forums, engagement with course materials, course and slide views, self-assessment quizzes (Conijn, Snijders, Kleingeld, & Matzat, 2017; Gkontzis et al., 2018; Nespereira, Vilas, & Redondo, 2015; Okubo, Yamashita, Shimada, & Ogata, 2017; Aguiar, Chawla, Brockman, Ambrose, & Goodrich, 2014),
- *course engagement and motivation*: pass/fail status, grades, assignments completed, student course history, reflections and self assessments, number of credits enrolled, and number of lost courses, attendance statistics) (Mitra & Goldstein, 2015; I.-A. Chounta et al., 2020; Carter, Hundhausen, & Adesope, 2015; Niitsoo, Paales, Pedaste, Siiman, & Tõnisson, 2014).

One can argue that existing IA solutions for identifying students at-risk do not follow a systematic or standardized approach regarding the selection and use of data. Instead, they are developed based on data of various types and different granularity. Additionally, the significance of the indicators mentioned above is dependent on the context, which consequently suggests that these indicators might not be applicable or appropriate for other contexts (Akçapınar, Altun, & Aşkar, 2019). If researchers and institutional stakeholders are interested in predicting student dropouts using IA, they may need an overall view of possible dropout indicators. Specifically, institutional stakeholders' viewpoints will be helpful since they are the ones who ultimately interpret the IA solution. This paper illustrates how to apply a systematic method to engage stakeholders and researchers in **identifying meaningful data and indicators to address dropout while still taking into account contextual factors**.

2.3 Stakeholder perspectives and adoption of Institutional Analytics in HEIs

Studies in IA focus on providing solutions for issues such as providing feedback for students or predicting student dropouts using student data (Nguyen, Gardner, & Sheridan, 2020; Herodotou, Naydenova, Boroowa, Gilmour, & Rienties, 2020). The adoption of these solutions depends on technological developments and the institutional communities that are typically the primary stakeholders. One of the main reasons for low adoption is the lack of involvement of stakeholders and the lack of shared understanding with the institutional community of LA (and consequently, IA) services (Sun, Mhaidli, Watel, Brooks, & Schaub, 2019; Aguilar, Lonn, & Teasley, 2014). Stakeholders often question the accountability and transparency aspects of the analytical services, especially when they involve advanced computational methods such as machine learning and artificial intelligence (Aguilar et al., 2014), thus discouraging the adoption of data-informed decision-making (Sun et al., 2019). To facilitate trust among the stakeholders, it is necessary to communicate what data we collect, with whom we share these data and how they are used (Sun et al., 2019; Clow, 2012). We argue that we can effectively address dropouts on the institutional level; that is, when institutional stakeholders – such as institutions' government, curriculum developers, administration and counseling services – have the necessary information, resources, and policies in place to supporting students who may be at risk. Providing stakeholders with information in terms of data is the first step. However, developing actions – and potentially cultures – in which institutional stakeholders and instructors see themselves as able to use this information to support students at-risk and work towards this goal actively is necessary (Yeager et al., 2019; Howell, Roberts, Seaman, & Gibson, 2018). To do so, exploring and documenting stakeholder perceptions is essential in order to increase the efficacy of IA solutions (Falcão et al., 2020; Dollinger, Liu, Arthars, & Lodge, 2019; Tsai & Gasevic, 2017).

The existing research focused on stakeholders' perspectives towards the challenges and needs for LA adoption (Hilliger, Ortiz-Rojas, et al., 2020a; Beer & Lawson, 2017), policies for collecting, analysing and protecting data (Hilliger, Ortiz-Rojas, et al., 2020b; Colvin et al., 2015), teaching staff expectations on LA services (Kollom et al., 2021), and the usage of early warning systems by academic advisors (Aguilar et al., 2014). Herodotou et al. (2020) investigated the students' perspectives on academic failure in relation to distance learning. Therefore, related to face-to-face/university-based learning, most of the previous studies are focused on the students and teachers perspectives on LA implementation in general (Hilliger, Ortiz-Rojas, et al., 2020a; Kollom et al., 2021) but not on a specif context such as LA adoption to reduce student dropouts (Falcão et al., 2020).

Several frameworks and instruments prioritize and focus on ways to support LA and IA adoption. In this line of research, the framework "Supporting Higher Education to Integrate Learning Analytics" (SHEILA) proposed materials, such as protocols for conducting surveys, interviews, and focus groups, for exploring stakeholder needs for LA services (Tsai, Scheffel, & Gasevic, 2017), and for supporting stakeholders' engagement. Related works explored the application of the SHEILA framework for identifying the stakeholders' needs related to LA adoption (Hilliger, Ortiz-Rojas, et al., 2020a). Similarly, LA-DECK – a card-based co-design tool – was specifically developed to support the inter-stakeholder design of LA innovations (Alvarez, Martinez-Maldonado, & Shum, 2020). The approach proposed by LA-DECK supports different stakeholders, even non-technical stakeholders or stakeholders without data-related knowledge, to shape LA developments (Vezzoli, Mavrikis, & Vasalou, 2020). For example, it contains cards related to the learning objective, analysis method, user interface, developer tools, data sources, privacy cards and so on, which users can select.

Other participatory and socio-technical approaches, such as co-design workshops accompanied by interviews, observations, or focus groups, have been explored as a means to integrate end-users' input into the technology-creation process (Liaqat, Axtell, Munteanu, & Epp, 2018; Gilliot, Iksal, Medou, & Dabbebi, 2018). Participatory and socio-technical approaches allow practitioners to reflect on what they are doing, why they are doing it, and how things could be done differently, and help researchers and developers to understand the implications of their work (Liaqat et al., 2018; Gilliot et al., 2018).

Few large-scale studies provide an agenda on LA adoption based on stakeholders' perspectives. These studies focus on how to use LA solutions to improve teaching quality, student experience and student learning outcomes (Colvin et al., 2015), as well as what kind of leader-ship approaches are suitable in the process of LA implementations (Dawson et al., 2018). The other agendas provide suggestions for data-informed solutions for addressing dropouts based mainly on existing literature (Ifenthaler & Yau, 2020; West et al., 2015). However, to the best of our knowledge, there is no agenda that identifies, documents and evaluates strategies that institutional stakeholders can design and that can be enhanced by IA solutions suitable for different types of dropout-related matters in HEIs. Our contribution aims to address this gap by actively **involving institutional stakeholders in the design of an agenda** that brings together the reasons behind dropouts, the data-informed solutions and the design of institutional strategies.

2.4 Research Questions

The main research question we aim to address is: *What are the perceptions of institutional stakeholders with respect to HE dropouts: factors influencing dropout and the role of the institution in reducing it with the help of IA?*. Under the main research question, based on the related work, we formulated the following sub-questions:

- **RQ1:** What are the academic stakeholders' perceptions regarding student dropouts? To answer this question we gathered information on the following;
  - To what extent do academic stakeholders consider dropouts to be a problem for study programs and the HEI overall?
  - What are the most important dropout reasons and patterns for study programs according to academic stakeholders?
- **RQ2:** What are the academic stakeholders' perceptions regarding the use of IA for addressing students dropouts? To answer this question, we gathered information on the following;
  - What data do academic stakeholders use (if any) to address dropouts, or what data do they perceive as potentially informative for identifying future dropouts?

- What are the strategies, policies, or individual practices established to address dropouts in study programs?

3. Methodology

We conducted this research as part of a large-scale project that aimed to develop an institutional dashboard to support academic stakeholders (students, teachers, counseling services, administration, and HEI government). The project was carried out in a public, Estonian HEI with nearly 13,000 students, including 1200 international students from 90 countries. The HEI consists of four faculties: the Faculty of Arts and Humanities, the Faculty of Medicine, the Faculty of Social Sciences and the Faculty of Science and Technology. One of the aims of the dashboard was to communicate student-related information to academic stakeholders, such as program directors and career counsellors, to support the early detection of students at risk of dropping out from their studies.

For designing the dashboard, we followed a participatory approach conducting a series of workshops to gather insight from the end-users. A participatory approach aims to directly and actively involve stakeholders in the design of a product (either this refers to a digital or tangible artifact or even a work process) to ensure that the final design will take the stakeholders' requirements and perceptions into account and that it will satisfy the stakeholders' needs (Kuhn & Muller, 1993; Kensing & Blomberg, 1998). Here, the task was twofold: on the one hand, we wanted to gather requirements on work processes and strategies for supporting students at-risk; on the other hand, we wanted to identify data-informed indicators that can support stakeholders in identifying students at-risk. The rationale was that the stakeholders are responsible for identifying bottlenecks, for redesigning academic curricula and for providing appropriate support to students. Therefore, they would be able to contribute with their experience and expertise in the strategic design of the IA infrastructure. We opened a call for the workshops, and 13 institutional stakeholders from five different specializations were selected to participate after volunteering. When choosing participants, we aimed at a representative population among bachelor and master curricula and faculties (see Table 1) and stakeholders' roles – in this case, program directors, academic specialists and study counselors.

Academic specialists are institutional employees (either faculty or administrative staff) who are involved in institutional level decision-making activities. Program directors are faculty members responsible for making decisions to support curriculum improvements and management. Career counsellors are qualified HEI employees who help students in making decisions related to their work and education, plan and develop their career and develop their job searching skills. In addition, we selected participants to represent all faculties, participants who were fluent in English, and participants who stated they had some basic knowledge about LA and dashboards.

During the workshops, we used a semi-structured interview protocol (See Appendix: 6) to guide the activity and to gain insights and information from the participants. The focus groups were conducted by an experienced researcher in Human-Computer Interaction who has conducted several workshops and focus groups using qualitative research methods. We conducted in total five focus groups for stakeholders from five specializations. By conducting the focus groups, we aimed to uncover participants' perceptions regarding dropout factors for this specific socio-cultural context and participants' needs for supporting students at risk. The main aim of choosing focus groups instead of individual interviews was to enable peer discussions on institutional strategies that could potentially reveal different perspectives and priorities among stakeholders. The rationale was that these discussions would allow stakeholders to reflect on existing practices, to pinpoint challenges and limitations that could halt the adoption of IA solutions and to envision benefits of this adoption while, at the same time, the participants would have the opportunity to be exposed to different perspectives and to elaborate using arguments from their own experience. At the end of each session, we discussed work strategies and collectively designed follow up plans of use for an early-alert intervention dashboard. In addition, we introduced a prototype of the dashboard to the participants (I.-A. Chounta et al., 2020; I. Chounta, Pedaste, & Saks, 2019). The aim was to collect ideas on work-routines with the dashboard and to design data-informed indicators that may suggest dropout risk.

To analyze the participants' input, we developed a coding scheme that reflected on the research questions of this work, and we asked two researchers to conduct the coding. Then, we analyzed the codes using LCA (Case & Light, 2011) in order to identify concepts or perceptions among academic stakeholders' opinions regarding student dropouts, factors that influence dropouts and ways to address them.

3.1 Data Collection

The focus groups were carried out from December 2019 to February 2020 in the selected university. The focus groups took place in the stakeholders' offices as planned after communication with them. Focus groups were face-to-face, and each focus group lasted around 90 minutes. Participants from the same specialisation (curriculum, or else, study program) were interviewed at the same time, thus resulting in five focus groups. To guide the discussions, we used an interview protocol (See Appendix: 6) that was designed based on the SHEILA framework [1] and it was adapted to align with the research questions and sub-questions

[1] https://sheilaproject.eu/sheila-framework/

presented in 2.4. We divided the questionnaire into three parts. The first part (PART A) aimed to collect information about the participants, such as their work experience rather than demographics since we sought to understand participants' attitudes towards dropouts which one can argue that it relates more to their professional expertise rather than their demographics (for example, gender and age). PARTS B (participants' perception about students at risk and academic data) and C (dashboard related questions) cover two research questions.

One researcher was responsible for conducting the semi-structured interviews and audio-recorded them with the informed consent of the participants. Additionally, the researcher kept handwritten notes. We transcribed verbatim the audio files obtained and juxtaposed them with the handwritten notes.

Table 1. Overview of the 13 participants who were involved in the study's 5 focus groups along with information regarding their faculty, institutional role (academic specialist, program director and career counsellor) and professional experience (in years).

Participant	Faculty/Department	Position	Years of experience in current position
ST.C1	Science and Technology	Academic Specialist	2
ST.C2	Science and Technology	Program Director	2
AH1.C1	Arts and Humanities	Academic Specialist	20
AH1.C2	Arts and Humanities	Program Director	5
AH1.C3	Arts and Humanities	Program Director	-
CS.C1	Counseling Service	Career Counsellor	1
CS.C2	Counseling Service	Career Counsellor	2
CS.C3	Counseling Service	Academic specialist	10
AH2.C1	Arts and Humanities	Program Director	20
AH2.C2	Arts and Humanities	Academic Specialist	20
AH2.C3	Arts and Humanities	Academic Specialist	20
M.C1	Medicine	Program Director	3
M.C2	Medicine	Academic Specialist	3

3.2 Data Analysis

To systematically analyze the interviews, we performed content analysis on the transcriptions (Maxwell, 2012). We defined four main themes aligned to the research questions: *"Whether participants perceive dropouts as a major concern or not"*, *"Dropout Reasons"*, *"Strategies suggested or established to overcome dropouts"*, *"Data that can be used to predict dropouts"*. Then, we analyzed the data to explore the relationships between themes and to identify potential sub-themes under each main theme.

We carefully reviewed all transcripts before the coding and summarized focus group responses into a spreadsheet to support the formulation of the coding scheme. For each one of the themes (both the main and sub-themes), we calculated the frequencies of occurring codes. Then, two researchers (co-authors of this work) double-coded all five foucs groups while systematically recording patterns and themes. We used an iterative approach where the coders performed three iterations during which they assigned codes, discussed their disagreements and formulated arguments to support their position. After the last iteration, we calculated the Kappa coefficient for all the categorical nodes (McHugh, 2012). We established a Kappa coefficient higher than > 0.75 for 50 codes out of 51. For the remaining code, Kappa coefficient was equal to 0.6. Ultimately, we took into consideration all categories with Kappa higher than > 0.6 (See Appendix: 5). The reader can retrieve the final version of the coding scheme at (See url: `https://tinyurl.com/f4dth23k`).

Finally, we performed Latent Class Analysis (LCA) on the codes extracted from the content analysis. Our goal was to identify the underlying relationships and structures among the different factors associated with student dropouts as evident by participants' perspectives (McCutcheon, 2002). Even though thematic analysis is a widely used technique in qualitative data, we selected content analysis due to its ability to quantify data by showing word patterns used in this context. LCA is a modeling method for identifying latent groups or subgroups based on pattern similarity in multivariate categorical data (Masyn, 2013). LCA is considered a 'person-centric' model that focuses on respondent patterns as opposed to 'variable-centric' methods such as factor analysis which is appropriate for continuous variables (McCutcheon, 2002). Here, we used LCA to identify latent relationships among dropout factors based on their similarity of participants' responses in focus groups. We selected LCA due to its applicability to categorical data, allowing us to identify sets of underlying subgroups of individual factors based on the intersection of multiple observed behaviors (Lanza & Rhoades, 2013), that is the participants' responses. Further, LCA results are not sample dependent and can replicate in other examples. At the same time, LCA is a widely used method in identifying reasons that contribute to high school dropouts (Boyce & Bowers, 2016; A. J. Bowers & Sprott, 2012) and in Education context in general (A. Bowers & Graves, 2018).

Figure 1. A diagrammatic representation of the research process

4. Results

This section presents the results from the descriptive analysis, qualitative analysis of the focus groups, the LCA analysis, and class interpretations based on the participants' perceptions.

4.1 Descriptive statistics on content analysis

Table 2 presents the codes' reference frequency; that is, how often participants mentioned the different codes during the focus groups. The results reflect the institutional stakeholders' perception of student dropouts and the diverse role of the HEI in dropouts. Most participants agreed that there is a high number of dropouts in every specialisation. However, participants were divided as to whether dropouts are a significant problem for the HEI (12) or whether dropouts are not necessarily a problem of the HEI (12). In the Faculty of Science and Technology (ST) 5 out of 12 statements declared dropouts as a problem of the HEI and seven (7) as not a problem of the HEI. ST has more students compared to the different faculties. Therefore, one could argue that the impact of dropouts is not as significant or "visible" for this faculty as for other faculties, of smaller size, and that this is reflected to the stakeholders' perception. Eight participants from Arts and Humanities (AH1.C1, AH1.C2, AH1.C3), Counseling Services (CS.C1, CS.C2, CS.C3) and Medicine (M.C1 and M.C2), provided the highest number of dropout reasons (Counseling Services=11, Medicine=10). Those participants belonged to faculties that had already designed, developed and established strategies, policies and individual practices to overcome dropouts. AH1.C1, AH1.C2, SC.CA3 (Arts and Humanities), M.C1 and M.C2 (Medicine) stated that their specialisations are less popular among the students. Participants from Medicine noted that lack of popularity contributes significantly in early dropouts. Therefore, they were concerned about establishing strategies to address student dropouts. AH.2 pointed out the usefulness of student data when designing such strategies. Our results suggest that the participants who have identified dropout patterns for their curricula have also reflected on strategies and policies to address dropouts.

Table 2. Frequencies of responses generated from content analysis for the four main themes of this study and per focus group.

Main themes	ST	AH.1	SC	AH.2	M
Dropouts are a major concern	12	5	3	3	1
Yes but not the HEI's problem	7	2	2	1	0
Yes, dropouts are the HEI's problem	5	3	1	2	1
Most important dropout patterns	8	7	11	5	10
Early Dropouts	1	2	2	3	6
Middle Dropouts	2	4	5	1	2
Final Year Dropouts	5	1	4	1	2
Strategies, policies or individual practices to address dropouts	3	10	14	1	6
Established	2	10	6	1	4
Suggested	1	0	8	0	2
Students data can be used to address dropouts	2	2	1	5	3

4.2 Participants' perceptions regarding student dropouts

To examine potential semantic structures and underlying themes in participant responses, we performed LCA to 51 codes generated from the content analysis (See `https://tinyurl.com/f4dth23k`). We started modeling with two classes, and subsequently increased the number of classes by one each time to ascertain the model with substantively meaningful interpretations and (Foti, Bray, Thompson, & Allgood, 2012) model fit.

Usually, it is difficult to determine the exact model fit in LCA based on one method (Masyn, 2013), and there's no one best method to select the latent class solution. Therefore, we calculated the Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC) and, log-likelihood (LL) and compared models to identify the best LCA model. Lower values of AIC (Akaike, 1974), BIC (Schwarz, 1978), aBIC and LL indicate better model fit. LL compares the fit of two models by examining how likely one model predicts the data compared to the other. In our analysis, the BIC (621.5513) was the lowest at the 1 class solution, and aBIC (534.7415) was the lowest at the 5 class solution. Based on LL values (56.7), the 12 class model had a significantly better fit. Therefore, we selected model 12 as the best solution after manually analysing and interpreting those three solutions.

The 12 classes are shown in Table 3. Since we conducted our LCA analysis for all the codes without separating to the RQ1 and RQ2 classes contains results related to both RQs. However, not both RQs results are available in all the classes. For example, class 1 only includes RQ1 (*"To what extent the participants consider dropouts as a problem for their institutes, programs and the university overall?"*) and (*"What do participants think are the most important dropout reasons and patterns for their institute /program?"*). At the same time, class 12 includes results addressing both questions; RQ1 (Academic adjustment of international-national students, Family issues, Political problems, Qualification-oriented targets, Perfectionism perceived by national students, RQ2 (Tax office data to collect personal information, Qualitative perspectives of reasons for dropouts).

Based on participants' statements, we manually grouped all the codes into two main categories, that is **Student Aspects** and **University Aspects** (Table: 3). By aspects, we mean both reasons and outcomes. For instance, choosing the wrong speciality is the student's decision and it will negatively affect the student themselves. Hence, it was categorised as a student aspect. On the contrary, the low completion rate of studies will affect the HEI reputation, and as such, low completion rate categories is a university aspect. Further, the strategies that the HEI can suggest or has already established (e.g Inform relevant people to take actions) are listed under the university aspects. After that, we grouped classes into 3 high-order levels based on the class similarities (Figure: 2).

We interpreted the derived classes - taking into account the four subsections in the two research questions - as follows:

- **Class 1-Personal dropout reasons**: Participants pointed out that students may, erroneously, believe they learned what they needed to learn and can find a good job without writing a thesis and acquiring a degree ([ST.C2] *"I think sometimes students think that they don't need to have the thesis anymore because now they have learned what they needed to learn to have found an excellent job and they don't want to spend the energy"*). Academic goals and motivation are the IA indicators which can use to identify dropout reasons under this category.

- **Class 2-Interest towards the subjects**: Dropouts may have both positive and negative impacts. Dropping out can be perceived either as correcting a wrong decision or as a problem. Wrong study choices are among the primary triggers for leaving HE. There are mainly two reasons behind wrong study choices: 1) students do not understand their interest until they start the program ([AH1.C1]: *We had somebody who had a master's in x. They came in to [study] y and then at the end of the first semester like they were doing fine, but they realized that they wanted to study for z and they left*); 2) due to low admission score, students may not be able to enroll in their preferred studies. Overall, wrong study choices are associated with negative completion intentions and dropouts.

- **Class 3-Curriculum alignment with satisfaction**: Misalignment of curriculum with industry's or students' expectations may lead to students' dissatisfaction. Participants stated that students who drop out believe their education would not benefit their future life.

  Concerning students' expectations, the number of dropouts for particular courses can indicate issues with the curriculum's structure. For example, suppose for a particular course the students drop out consistently. In that case, it may be necessary to re-think its position in the curriculum – that is, when and under what circumstances it is offered. At the same time, it is essential to align the purpose of the HEI and the expectations of society. One solution is to involve external stakeholders in the curriculum development to understand their needs, especially for technology-related disciplines ([ST.C2] *"We probably have to include the industry people much more to understand better what they want from us."*. To understand curriculum related issues, student feedback can be consider as an IA indicator.

  Participants pointed towards the importance of peer mentoring. According to the participants' experience, there are situations that students decide to go for a particular specialisation, and after several weeks they drop out. After talking to the students, they mentioned that *"it is not easy to get understanding [in] this one big discipline"*.

- **Class 4-Institutional support towards students' goal commitment**: Students' goals and commitment have a significant impact on dropouts. Some students enter HEIs with clear goals, and usually, the first choice of admission reflects this.

Table 3. Overview of the classes derived from the LCA analysis. For each class, the factors are grouped according to whether they are student or university-related, and the number of codes (NC) belongs to the class is provided.

No	Class Name	Student Aspects	University Aspects	NC
1	Personal dropout reasons	Students self-motivated intentions to dropout		1
2	Interest towards the subjects	Wrong speciality	Lack of alignment between personal and curriculum goals	2
3	Curriculum alignment with satisfaction		Talk to students, Curriculum development	2
4	Institutional support towards students goal commitment		Identify study priorities/Choices made in the admission, Inform relevant people to take actions	2
5	Individual academic struggles	Individual learning difficulties, Low grades and failed courses		2
6	Professional and financial concerns	Financial issues, Employment		2
7	Academic integration	Opportunity to transfer, Admission score, Credits for next and previous semester, Next semester payments	Misused opportunities	5
8	Student well-being	Uncertainty about future professional opportunities, Health issues, Extracurricular over-involvement	Adapt /raise awareness to the student background, Detecting/monitoring less engaged students, Academic support programs	5
9	Faculty-student relationship	Report on not-interesting study paths	Supporting students is an institutional responsibility, Counselling, Group discussions, Waste of investments due to dropouts	6
10	Social support and sense of stability	Psychological issues, Social issues, Less support from university, Study results	Keep track of graduates and dropouts, Encourage student-supervisor communication, Level of the university	7
11	Curriculum related difficulties	Hard curriculum, Struggling with thesis, Negative student-supervisor relationship, Extreme workload, Course registrations, Academic leaves	Seminar and courses, Study and self management skills	8
12	Personal and contextual aspects	Academic adjustment of international-national students, Family issues, Political problems, Qualification-oriented targets, Perfectionism perceived by national students	Tax office data to collect personal information, Qualitative perspectives of reasons for dropouts, No negative consequences after dropout, Benefits from degree completion	9

Thus, admission choice can be a predictor of dropout in the early stage of studies. Taking into account students' admission choice, academic stakeholders can initiate discussions regarding students' choice of specialisation: ([AH1.C1] *If somebody is not doing well, I communicate with the program manager or program director usually; If it's a first-year student, I still contact the members of teaching staff and, and ask whether the student has been in seminars and prepared for the seminars, and so on*).

- **Class 5-Individual academic struggles**: Learning is a factor that determines students' persistence. Some students need more time than others to accommodate with academic life. Students who begin studying without understanding or being aware of their abilities may get frightened by the demands of academic life ([M.C1] *since they're not expected to do that much during the semester, and then at some point their workload may skyrocket*). The student's pass/fail status and course completion level are potential data indicators for predicting a student's academic struggles.
- **Class 6-Professional and financial concerns**: Participants suggested that employment is one of the most prominent reasons behind student dropouts. Some students intended to work full-time instead of following full-time study programs. As a result, students who spend more time working outside the HEI and have a paid, full-time career are more likely to leave the university compared to those who do not work or work on a part-time basis ([AH1.C1] *If you have a job and studies, and sometimes you feel that [it is] too much*). Therefore, employment and financial status of the students may help identifying risk of dropping out.
- **Class 7-Academic integration**: This class emphasizes the importance of dropouts for the institution. Even an early

dropout constitutes a significant concern and can be perceived as a wasted opportunity; ([AH2.C2] *"Well, it is a problem also because they took the place of somebody else."*).

Students may apply for some disciplines (e.g., Medicine or Engineering) due to professional prestige and attractiveness. However, due to competition, ensuring a study place in these curricula is difficult and many students eventually choose another specialisation where they can secure a spot. ([M.C1] *"Some of them have a very clear vision that they don't want to be profession X, but somehow they did not get in to become profession X, and they come here. Some of them decide to graduate as profession Y. But most of them will try again and again to become a profession X."*). Students who are uncertain about their choice, and their future professional image are likely to look for opportunities to change their study program. This is common in early stages of studies.

There's a clear connection between students' decisions and credits. If the student considers transferring to another program, the time and effort they invest in their current studies may be low. Thus, the number of credits covered in the past semesters and the registered credits for the following semesters can provide valuable insights regarding dropouts ([AH2.C2] *"I looked into how many credits they have, what are the registration for next semester."*). Good admission grades may show students' knowledge alignment with their selected specialisation and can be used to identify dropouts ([AH1.C2] *"think it would be good to see admission score."*).

- **Class 8-Student well-being**: Uncertainty about the future study benefits is a prevalent issue. If the specialisation is not popular, or if students do not have a clear picture about the potential career opportunities, this may lead to depression, disengagement, and eventually dropout ([M.C1] *"I think this profession is not very well known in our society. Plus their professional competency activities. What they actually can do after graduation, it is not very well known"*). Additionally, students' workload and health issues may negatively affect students' well-being while pursuing a degree.

  Participants requested information regarding students' academic background to decide whether it contributes to student struggles. In this way, study counsellors can address the issue by providing academic support programs, especially for less-engaged students. Specifically for the students who are uncertain about their future, the academic support programs can help them clarify their future career paths ([AH1.C2] *"With the support programs, the student would better understand what it means to study philosophy in this department. Because if they don't have X at high school, they may not know anything. If they had X in high school, they might have a very different experience from what it's here."*).

- **Class 9-Faculty-student relationship**: Participants stated that student dropouts could be a wasted investment for the HEI. For example, students who drop out in the last stage of their studies without completing their thesis ([ST.C2] *We invested a lot of energy by teaching them. And in principle, it was okay because the industry is benefiting from it. But, [we] don't benefit from it*).

  Sometimes, students do not know how to navigate their studies which may lead to energy loss or tiredness over time. Likewise, students get disappointed with the subject contents or teaching arrangements and conclude that university education does not correspond to their expectations ([ST.C2] *"Because they might decide, okay, let's do something different."; "Just tired from same subjects."*). In this case, HEIs can support students by arranging counselling sessions, and group discussions.

- **Class 10-Social support and sense of stability**: Based on the level of the curriculum, the risk of dropout may change. If the curriculum is small and the number of students is limited, dropout is a significant concern from the HEI's perspective. At the same time, participants welcomed dropouts during the first study year and due to students' wrong choices. In this case, participants do not require any support to prevent dropouts.

  If the students fail to satisfy their social and psychological needs, it may negatively influence their performance and the motivation towards the studies ([AH1.C1] *"They may also have social problems, for example. They moved to a new place. They don't know all the other people so long ago. These are sort of social personal skills."*); ([CS.C1] *"The student has been like a little bit shy or whatever other reasons haven't asked for proper help or guidance from their Institute. And those kinds of students who were not able to ask or make it noticeable that they need help or guidance...."*). This situation may lead to dropouts if the HEI is not able to identify students' needs.

  Participants stated that students' aspirations might increase if student-supervisor mentoring relationships are encouraged. If the student is avoiding lectures or meetings with supervisors, institutional stakeholders should communicate with students, and even encourage the supervisors to pursue communication with the students ([AH1.C1] *"It may have been even more useful than me (academic specialist) writing them, to have the supervisors write to them."*). Supervisors can effectively influence students by providing social support, sense of stability and belonging required in the student's academic life. Participants also stated that by keeping track of students' yearly progress towards the graduation, they can identify the students in need.

- **Class 11-Curriculum related difficulties**: Students may discover that the academic program is more complicated and competitive than expected ([CS.C3] *"Sometimes there are tough subjects, and it is not good if students selected those subjects early in their studies"*). Participants reported that students might lose interest when they have to follow courses and labs regularly. Another concern is thesis-related struggling which may contribute to students dropping out at the end of their studies. For example, students may struggle to find an exciting topic or a supervisor. Participants believed that students' active engagement with the thesis depends on the relationship with the supervisor. On the other hand, students may give up on their thesis due to poor time management, disappointment due to external factors such as low grades or because they perceive the thesis as demanding and challenging.

  Participants mentioned that to overcome study-related struggles we need to establish interventions on study skills and self-management skills ([CS.C1] *"We think about the first year; it's really important to support them in [acquiring] study skills and self- management skills."*).

  Due to the aforementioned difficulties, students may feel overwhelmed and they tend to take academic leave. This does not necessarily mean that all students take academic leave due to academic life struggles. For example, there are students who use academic leave while serving in the army. Thus, before making decisions based on academic leaves patterns, it is necessary to investigate the underlying reasons ([AH1.C1] *"Academic leave even saying student don't have kind of strength to go on."; "For example, in the case of academic leaves, some students take leaves for serving in the army. I guess these academic leaves risk-free."*). Other than academic leaves, participants considered course registrations as a good dropout indicator. By checking the number of courses students registered for the next semester, the institution can be aware whether the students have enough credits for the semester. If not, take actions to avoid potential issues.

- **Class 12-Personal and contextual aspects**: This is one of the largest latent classes, representing nearly ten codes. The participants who reported those codes have diverse perceptions regarding dropouts. The main perception was that dropouts are a global political problem rather than a problem of HEIs ([ST.C1]*"It is not even the university's problem. It's a political problem everywhere in the world"*). They further elaborated that because many external factors affect dropouts, it is difficult for the HEI to intervene. For example, citizenship or residency of students is usually considered a concern regarding dropouts. Participants stated that international students might have a higher dropout probability than nationals because nationals are familiar and comfortable with the current lifestyle or environment. Nonetheless, there are cases that national students leave the university due to family or other commitments ([ST.C1] *"It does not make sense to mix it because the international students have indeed very different sort of problems than the Estonian students. And if we want to solve problems, then we have to know about the different kinds of issues."*).

  Participants believed that if the students are working or they leave the university to pursue other opportunities, there is no point in holding them back ([AH1.C2] *"The students who have chosen the wrong specialty mainly drop out during the first year. It is good for them to drop out because that would enable them to start again. There's not a huge loss."*). However, some participants argued that it is always good to complete the degree to move forward in the job market ([ST.C2] *"It's not a matter whether they're getting or not a job; it's more like being promoted or getting leadership positions"*).

  The participants who belong to this class do not provide positive feedback towards the quantitative indicators. They said that it's necessary to collect qualitative information to have a thorough understanding of the situtation. At the same time, they pointed out that the information coming from SISs is not enough to identify students at risk. There are cases where students do not provide accurate data as input. For example, students may hide their full-time employment status since the university does not allow it. At the same time, they agreed that it is not possible to force students to give accurate information. One possibility is to collect information from the tax office. However, to go into that direction, at the moment, there's no government support for the university to collect tax office data, and there will be data privacy concerns as well.

5. Discussion

Our study results confirm the findings of Tinto (1975) that dropping out does not relate to only one student aspect (for example, students' lack of commitment or motivation). We identified 12 distinct classes based on LCA. Then, we further grouped these classes into three levels taking into account related literature (Figure 2): Institutional Experience, Educational Goals and Personal Aspects. Our findings align and confirm existing theoretical and methodological frameworks related to reasons for student dropouts (Spady, 1970; Tinto, 1975; Cabrera et al., 1992). However, our findings provide more insights on which IA indicators align with different types of dropout reasons and what kind of strategies are suitable to eliminate dropouts.

Barefoot (Barefoot*, 2004) emphasized the importance of focusing on the institutional experiences regarding work practices and policies, the way of providing advice and designing course and curriculum structures. Our work supported the arguments

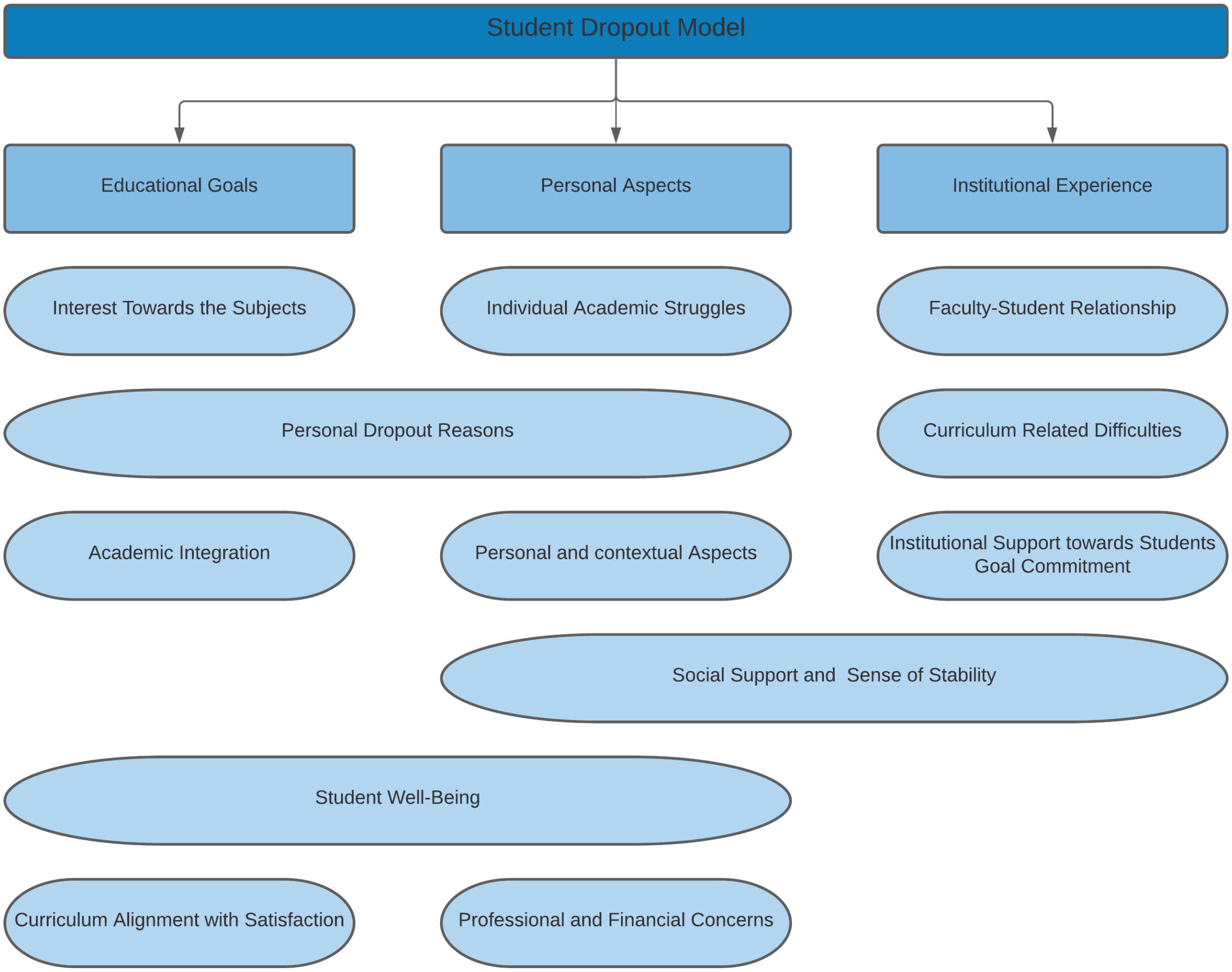

Figure 2. Student dropout model

established by (Barefoot*, 2004) deriving four categories that prioritized the students' institutional experience regarding dropouts. Other studies included factors such as institutional financial capability (Gansemer-Topf & Schuh, 2006)), and the size of the institution (Ryan, 2004). However, no significant relationship between the above characteristics and student dropouts was established (Titus, 2006).

Regarding educational goals, our findings correspond to the findings of Hovdhaugen (Hovdhaugen, 2009) and Pascarella (Pascarella & Terenzini, 1991). According to (Pascarella & Terenzini, 1991), having clear educational goals reduces the chances of dropping out. The results of our study emphasized another aspect of this argument: *the students with the clear educational goals who are not satisfied by their current study program may be likely to drop out*.

According to Vogel (Vogel et al., 2018), dropouts may be attributed to personal aspects like demographics, family status, health or financial concerns (Vogel et al., 2018). Our findings confirm the role of personal aspects in dropouts (for example, health problems were mentioned by the participants as factors that affect students' well-being). Besides, individual academic struggles may affect dropouts according to academic stakeholders.

Having said that, the reasons for dropping out of studies cannot be viewed as a single category. Therefore when addressing dropouts, interventions cannot follow a "one size fits all" approach and we need to establish separate plans for action to overcome institutional, educational and personal issues.

The following two sections provide an agenda on addressing student dropouts by improving three main aspects identified from the study. The agenda includes what the dropout indicators are and what strategies can be implemented to overcome dropouts and increase student success.

5.1 Academic stakeholders perceptions regarding addressing student dropouts

This section presents how to address Institutional, Educational and Personal issues in general and with the use of IA. We triangulated our findings with related literature.

5.1.1 Addressing student dropouts by improving institutional experience

Since dropouts are an issue globally, institutions adopt various strategies to address them. Those strategies vary based on the available resources, the students' needs and the institutional expectations. According to academic stakeholders, there are different ways that institutions can influence dropouts. Previous research also emphasised that the risk of dropping out is not an inherent quality of the student but can be a function of the interaction between student and university (West et al., 2015).

Out-of-class retention programs are one of the ways to motivate first-year students. HEIs offer various programs such as campus orientations, community services, language programs, events to build institutional spirit, cultural events and programs for finding lodging (Barefoot*, 2004). The main goal of such programs is to increase social and institutional integration. The ongoing orientation programs and seminar courses can enhance the likelihood of retention, especially for first-year students who get the opportunity to adjust and integrate into the new academic environment. Students' "sense of belonging is another dimension where HEIs can support students by providing academic and social support under challenging situations. Learning communities, that is small communities where students can register for the same courses, are another type or orientation program suggested by Tinto (Tinto, 1975) that supports interaction among student and provide several other benefits, such as students' being able to track deadlines and receive personal support.

Study and self-management programs can improve the students' study habits, time management skills and introduce them to campus resources (library, help centers). If the university encourages students on their achievements, students will be motivated to complete their studies. Many HEIs are establishing retention initiatives for at-risk students by offering 'early-alert' interventions. For example, during the beginning of the semester, poorly performing students are contacted and referred to tutoring or counselling services (Barefoot*, 2004).

HEIs can potentially focus on retention by appointing specialized staff having as primary responsibility student dropouts. Timely support and feedback are necessary for students' motivation. Related studies emphasised the importance of feedback, but at the same time, those studies stated that 50% of teachers do not provide students with feedback (Barefoot*, 2004). Based on the participants' statements, communication between students and supervisors can positively impact students' decisions. If teachers and supervisors can support interactions with students, students' institutional experience and persistence may improve.

5.1.2 Addressing student dropouts by supporting educational goals

If the students are dropping out due to particular study subjects or wrong study choices made by the students, identifying those students at the beginning of their studies can help to guide them.

Motivation and student choices are essential aspects to understanding dropouts and transfers. Tinto (Tinto, 1975) stated that students' commitment towards a particular institution or personal educational goals have strong predictive power. High-performing students may leave the university due to the not interesting (boring, or not satisfying) subjects, lack of academic challenges and the desire to transfer to another program. To overcome such issues, HEIs need to find strategic approaches which can influence students' transfers of dropouts, such as restructuring study programs. According to (Tinto, 1975) and (Pascarella & Terenzini, 1991) students' study behaviour, that is students' activity inside and outside the classroom, has a significant impact on the transfers. However, student engagement does not only depend on the students. HEIs should also strive to influence students' attitude towards learning by facilitating a learning environment that satisfies students (Hovdhaugen, 2009). HEIs should investigate methods that encourage student activity and engagement, especially by promoting communication and addressing the occurrence of misconceptions.

5.1.3 Addressing student dropouts by offering support to overcome personal issues

Other personal issues that may contribute to student dropouts include the pursue of better opportunities, and students' inability to cope with courses due to lack of background knowledge or motivation. For students who struggle with learning difficulties and extreme workload, universities can intervene to help. In some cases, HEIs can support students with personal decisions. For example, if the university can understand why students are demotivated and transfer to other disciplines, counselling sessions might be helpful. If students are suffering from mentally disturbing issues, individual study plans and academic leaves would be beneficial (Worsley, Pennington, & Corcoran, 2020). Finally, financial aids such as subsidised loans, and scholarships, may help students to focus on studying (Chen, 2012).

5.2 Academic stakeholders perceptions regarding the use of IA for addressing students dropouts

Early identification, and deep understanding of dropouts are essential for catering to students with the right solutions at the right time. IA have the ability to provide reliable predictions to address at-risk students. Further, IA can give adaptive and personal planning recommendations by monitoring student behaviours. To promote effectiveness, IA should target institutional facilities as well where student behaviour occurs (Sønderlund, Hughes, & Smith, 2019). At the moment, universities cannot address the issue due to the lack of information on how to address dropouts' problems. In other words, there is no way to retrieving the information in a meaningful way such as which students are intended to dropout, when and why. Therefore, IA is one of the solutions to overcome this issue.

5.2.1 What IA can offer to overcome issues related to institutional experience

The main aim of using IA for improving institutional experience is to identify students' issues and provide appropriate guidance. In brief, there are four main strategies to support retention of different student populations (West et al., 2015). 1) At the end of the semester; to inform or reach out to students who failed courses; 2) During the semester; to provide focused outreach, identify under-engaged, under-performing and over-challenged students; 3) At the beginning of the studies; to identify students potentially at-risk and provide targeted support and development opportunities; 4) Inform course design and delivery in general. Nevertheless, to provide useful advice, IA should learn at which circumstance students need support.

Some students may perform well overall, but they decide to drop out due to a specific subject. In such situations, there's a necessity to have a comprehensive look on *curriculum* to understand specific subjects that may pose difficulties for the majority of students (De Silva, Rodríguez-Triana, Chounta, Tammets, & Shankar, 2020). If IA can provide information regarding the curriculum – including risk indicators, such as completion time and retention rates – program directors can take further action. Other than the curriculum level improvements, instructors can provide personalised comments, and feedback to motivate students, and use early alert tools to improve *course* design and delivery(Star & Collette, 2010). The instructor-student relationship can further improve if IA can provide awareness for the instructors when students behave differently from peers (Tarmazdi, Vivian, Szabo, Falkner, & Falkner, 2015).

To improve the *overall institutional experience*, HEIs should consider offering dual support to teachers and students alike. Program directors may take action to oversee student issues without limiting them to one aspect, such as learning issues. This can be achieved by using machine learning and predictive modeling to identify various factors or aspects that affect dropouts (Arnold & Pistilli, 2012; I.-A. Chounta et al., 2020) and then, presenting this information to institutional stakeholders in the form of feedback on their curricula. This feedback can be used to guide students in seeking help or suggesting changes the students have to make to achieve their goals. In many situations, students are not fully aware of unproductive behaviour patterns and, even if they know, they do not know how to react or change them. Thus, with IA, the HEI can provide an action-oriented approach, personalized for each student's needs early in their studies.

When implementing IA solutions, it is necessary to consider the data collection processes we employ. In terms of data requirements, there are two aspects we need to consider. The first one is to explore existing data sets, such as data available in SISs or LMSs. The second is to combine quantitative with qualitative data, such as student feedback to synthesize and triangulate information from various sources. Based on the participant statements, student data such as course details, grades, registrations (presented in Table 4), can be used to assess the dropout risk.

Table 4. Dropout predictors related to Institutional Issues

Class Name	Dropout Predictors Mentioned by Participants
Social Support and Sense of Stability	Study Results
Curriculum related difficulties	Number of times students get registered for courses, Academic Leaves
Faculty-Student Relationship	Feedback
Institutional Support Towards Students Goal Commitment	Study Priorities/choices made in the admission

5.2.2 What IA can offer to overcome issues related to educational goals

Curriculum improvement is one of the main suggestions for avoiding dropouts related to educational goals. However, curriculum improvement is a long-term process. A short-time solution would be to identify students likely to drop out. Previous literature does not provide explicit suggestions on how to overcome this. We argue that we can use IA by designing computational predictive models that take into account factors representing Educational Goals such as admission score and low completion rates, credits for next and previous semester, subsequent semester registrations and so on.

If most students are dissatisfied with the curriculum, it is necessary to look over the issues and improve the curriculum in the long term. When implementing an IA solution to overcome the problems at the course level, we need to consider data related to course enrollment, student grading and student progress. Program-level data such as course selections, curriculum maps and student outcome matrix regarding students development of core competencies could be further used. For example, the Risk Management Model developed by Wong et al., (Wong & Lavrencic, 2016) shows interactive visualisations of student flows through the academic programs and the Visualised Analytics of Core Competencies helps students to learn their competency attainments (Chou et al., 2015) while Hilliger et al., (Hilliger, Aguirre, Miranda, Celis, & Pérez-Sanagustín, 2020) provide reflections on students' core competencies and proficiency levels. With the support of such tools, students may understand and reflect on how their study program and their own competencies match with their future work-life goals. Further, program directors can receive insights on the areas that need improvement, such as identifying the curriculum's impact on job opportunities, and aligning with industry, competitors and social requirements.

5.2.3 What IA can offer to overcome personal Issues

We need to identify the student population correctly to support students with everyday personal issues. However, due to privacy issues, providing data-driven solutions to address students' problems is unattainable. To that end, we can conduct surveys to collect data regarding the students' opinions related to personal problems. For example, HEIs can model real-time teaching and learning activities by collecting static and dynamic data of learning behaviour and content for students who are struggling with learning . These feedback loops can enable student monitoring and positively influence students' relationship with the institution. Since students' generics skills change over time, it is important to monitor learners' progress and level of competencies continuously. Then, intelligent recommendation interventions based on the real-time modeling procedures can be considered as a solution for struggling students (bin Mat, Buniyamin, Arsad, & Kassim, 2013; Papamitsiou1 & Economides, 2015; Akçapınar et al., 2019). Eventually, HEIs can potentially provide personalised feedback about the students' strengths and weaknesses as well as guidance for support services, such as tutoring, mentoring and learning communities.

When implementing IA to support students' personal aspects, one of the critical considerations is interpreting statistical measures depending on the student-related context value and culture. Therefore, it is necessary to focus on constructive approaches, such as bench-marking, when making decisions. For example, the healthcare industry uses analytics to evaluate the service effectiveness by considering the average time patients stay in the hospital. But, the extended stays can be interpreted as either "ineffective" or as "high quality" (patients do not discharge until fully recovered). This simple indicator can convey different meanings in different contexts. Likewise, those arguments apply to social dimensions in education. For example, if we select the international-national cluster as a dropout predictor, one may argue that international students tend to drop out due to the problems they face because they move to another country (such as difficulties in finding a place to stay, financial issues). At the same time, the argument could be reversed as international students are much more focused on their studies compared to the students in the host country since they are motivated to return to their home country.

5.3 Theoretical and Practical Implications

Based on the agenda we proposed, HEIs can gain understanding regarding the IA solutions that they should develop and the actions to take in different circumstances, such as dropouts related to personal, educational or institutional aspects. Even though there are previous studies related to identifying dropout factors, this study is significant because it provides insights on institutional stakeholders' perceptions of the IA solutions, data and the steps to address dropouts. These insights further confirm the added value of IA to different stakeholders and the ample possibilities for action that IA can provide to institutional stakeholders. Based on the results, we can clearly understand that institutional stakeholders are willing to have guidance on the decisions they have to take when students are at risk of dropping out. Therefore, the suggestions and recommendations provided by this study and the rationale behind them can improve IA's acceptability within HEIs and among the institutional stakeholders.

While earlier research has reported the importance of early-alert interventions, the lack of research regarding institutional stakeholders' viewpoints in IA applications is a substantial concern (West, Luzeckyj, Toohey, Vanderlelie, & Searle, 2020). Previous literature highlights the importance of stakeholder perspectives regarding the use of IA. Although the IA developments are promising (Luzeckyj et al., 2020), those initiatives are not widely adopted due to the lack of understanding among the institutional stakeholders who are going to use them. Even the current studies related to stakeholder perceptions mostly consider the student's perspective (West et al., 2020). However, students are not necessarily capable of solving their issues by themselves and it would be advisable to ask for institutional involvement when seeking to help the student. Thus, this study ensures that early-alert interventions serve the needs of the institutional stakeholders, and correct interventions can positively impact student success and reduce dropouts. Another challenge in developing IA solutions is to identify what are the indicators to be considered (Vossensteyn et al., 2015). As a solution, this work promotes a shared understanding and agreement between researchers and institutional stakeholders when developing early-alert interventions to identify students at risk. This shared understanding can reach by putting the stakeholders in a loop where institutional stakeholders bring their needs and perceptions related to dropout indicators, inform designers to build IA solutions and further evaluate the solutions by researchers.

Related studies conducted in Estonia (I.-A. Chounta et al., 2020; Niitsoo et al., 2014; Kori, Pedaste, Altin, Tõnisson, & Palts, 2016) mainly focus on student-facing dropout factors – that is, on factors that relate to student's practice, background or performance and do not take into account institutional aspects. Our findings confirm that student dropout is often related to the combination of reasons that include individual and curriculum-level factors, as suggested by (Kori et al., 2016; I.-A. Chounta et al., 2020). At the same time, institutional stakeholders pointed out that certain indicators such as time spent on studying or prior performance (Niitsoo et al., 2014) may provide insights regarding the risk of dropping out but should be interpreted with caution and in context.

Finally, it is essential to point out that human intervention is always necessary when making decisions and interpreting data to address student dropouts based on the IA solutions. Since not all dropouts can be interpreted as adverse decisions, the voluntary dropout can allow the student to follow new possibilities, such as finding a more appropriate path. A Practical implication is that universities should be careful in making decisions based on the IA outcomes that benefit students in achieving or acquiring a degree. With the early-alert interventions, institutional stakeholders get the opportunity to look at the student status and send reminders for student tasks (e.g. course registrations, payments, etc.). If the student cannot do the necessary activities even after informing, institutional stakeholders can talk with them and help them.

Our findings support, validate and strengthen related research. In addition, we envision that our study contributes to the scaling of IA across the HEIs by addressing the issues related to collecting, analyzing and reporting data and to institutional processes, organizational structures and facilitatory roles that should be further developed on the institutional level as a means of addressing dropouts in Higher Education. In particular, our study highlights the following two points: a) that the institutional stakeholders perceive as crucial the use of IA solutions to support in their decision-making, and; b) that the institutional stakeholders are aware of the potential of IA and they perceive IA as a valuable tool for addressing dropouts.

6. Conclusion

Identifying students who may drop out from HEIs and reducing dropouts is an important and challenging task for HEIs. The present study explores the HEI stakeholders' perceptions towards dropouts, and the established and suggested strategies for addressing dropouts in HE. The HEI dropouts cannot be interpreted in isolation from contextual factors. According to our findings, three main factors are contributing to dropouts (namely, institutional experience, educational goals and personal aspects). Some of them can be influenced by HEIs but others are beyond their scope (e.g., personal and social factors). Then, we mapped the problems to be addressed (according to participants) to existing theoretical and data-driven solutions to support evidence-based decision-making in relation to dropout management. Finally, building on the stakeholders' perceptions of dropouts, we proposed a participatory agenda for IA decision-making considering various stakeholder groups (program directors and academic specialists). Due to the participatory and focus group approach, participants discussed different strategies coming from different perspectives. In addition, we saw that the program directors and academic specialists had different understandings and perspectives regarding who could be at risk, why it is crucial, and how to address it.

We envision that the proposed agenda will enable HEIs to effectively address a policy issue, as student dropouts, to help them implement institutional processes and to develop facilitatory roles among the stakeholders dealing with personal, educational, and institutional issues affecting dropout. We argue that this work can provide insights regarding the use of IA for designing data-enhanced solutions, such as institutional dashboards, for addressing student dropouts and providing the means to institutional stakeholders for timely, evidence-based decision-making. This study is a part of a large-scale study which is planning to develop an early warning system. Therefore, we aim to discuss the implications of our results with the developers to decide how to incorporate identified indicators in the the IA solution and include information in the intended dashboard.

While previous research often focuses on single and specific dropout problems (Nguyen et al., 2020), we provide a broader view, identifying and addressing dropout factors at the institutional level that may be transversal to different institutions. Following the recommendation by Ifenthaler (2020), this paper further explores why and how students drop out due to different reasons and how IA can help to identify those cases in an early stage. In this study, we focused on institutional stakeholders since they are the ones who provide support strategies for students to retain and succeed in their studies. Moreover, by working with different types of students for long periods, they have a good understanding of the factors that may influence student dropouts. Therefore, we perceive institutional stakeholders as an important source of information for identifying students at risk and designing appropriate strategies for addressing dropouts. Furthermore, the new technological innovations can be unclear and can disrupt existing practices that institutional stakeholders follow. However, to obtain a thorough understanding and develop a robust and holistic strategic approach for addressing dropouts in HE, future research should also investigate the perspectives of students, instructors and developers. In future work, we also plan to address the limitations of this study. Due to the relatively low sample size, the findings can not be generalized across the HE sector. Therefore, we aim to validate and generalize our findings by expanding this work to include other stakeholders and institutions as well as collecting additional data. Further, cross-validating our results with documented dropouts and validation and triangulation of findings using other appropriate methods such as Epistemic Network Analysis (Zörgő, Swiecki, & Ruis, 2021) will strengthen the outcomes of this work.

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Declaration of Conflicting Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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1. Appendix A: Codes

Table 5. Codes generated from content analysis

Code	R1	R2	Kappa
Student Dropouts are a major concern or not			
Students Self-Motivated Intentions to Dropout	6	6	1
Political Problems	1	1	1
No negative consequences after dropout	4	4	1
Benefits from Degree Completion	1	1	1
Qualification-Oriented Targets	1	1	1
Lack of alignment between personal and curriculum goals	5	5	1
Supporting Students is an Institutional Responsibility	2	2	1
Waste of Investments due to dropouts	3	3	1
Misused Opportunities	1	1	1
Level of the University	1	1	1
Reasons for dropouts			
Uncertainty About Future Professional Opportunities	2	2	1
Report on Not-Interesting Study Paths	4	4	1
Opportunity to Transfer	3	3	1
Wrong speciality	6	6	1
Extreme Workload	1	1	1
Family Issues	2	2	1
Financial Issues	2	2	1
Health Issues	1	1	1
Psychological Issues	1	1	1
Social Issues	4	4	1
Hard Curricular	6	6	1
Individual learning difficulties	3	3	1
Less Support form University	1	1	1
Employment	8	7	0.6
Struggling with Thesis	3	3	1
Negative Student-Supervisor Relationship	1	1	1
Perfectionism Perceived by National Students	1	1	1
Strategies established and suggested to address dropouts			
Detecting/Monitoring Less Engaged Students	1	1	1
Counselling	1	1	1
Academic Support Programs	3	3	1
Inform Relevant People to Take Actions	6	6	1
Keep a track of graduates and dropouts	1	1	1
Encourage Student-Supervisor Communication	1	1	1
Talk to students	12	11	0.84
Seminar and Courses	4	4	1
Study and Self Management Skills	2	2	1
Curriculum Development	6	6	1
Group Discussions	1	1	1
What data can use as an indicators			
Course Registrations	3	3	1
Study Results	2	2	1
Tax Office Data to Collect Personal Information	1	1	1

Table 5. Codes generated from content analysis

Code	R1	R2	Kappa
Qualitative Perspectives of Reasons for Dropouts	2	2	1
Adapt /Raise awareness to the student background	1	1	1
Identify Study Priorities/Choices Made in the Admission	4	4	1
Academic Leaves	7	6	0.72
Admission Score	1	1	1
Extracurricular Over-Involvement	2	2	1
Credits for Next and Previous Semester	2	2	1
Low Grades and Failed courses	3	3	1
Next Semester Payments	1	1	1
Academic Adjustment of International-National Students	2	2	1

2. Appendix B: Interview Protocol

The time for the activity is about 90 minutes.

- Prior to the focus group session
  - Thank participants for their participation, remind them of the purpose and context of the activity
  - Introduce them to the participatory approach challenge of the workshop
  - Give details about duration, and data collection, introduce and walk through the consent form, ask for permission to record
  - Ask whether there are any questions
- During the focus group session

Table 6. Interview protocol

SHEILA Aspects	Questions
PART A: Information about participants – Please introduce yourself Duration: 10 minutes	
Identify key stakeholders	• Information about their work (experience, requirements) • What is your background • How exactly does your position relate to the *name* study curriculum • How long are you in this position Information about their work (experience, requirements)
PART B: Participants' perception about student's at risk and academic data Duration: 45 minutes	
Map political context and identify desired behaviour changes	General stance regarding students at risk (is it a problem? To what extent should we bother, how could we help) • Do you worry about students' dropping out of their studies? Would you still be willing to help in their studies? Why? – If yes: Do you usually try to find out the dropout rates for your curriculum? Is there any tool support? Does it worry you? Do you try to find out why? What do you do about it? Do you intervene? What kind of information would you like to have about the students who might be at risk? – If no: why not? What should we do -or not do -instead? Would you still be willing to receive information about students' dropout rates or not? – If yes: proceed – If not: what was your reason for participating in this workshop?
Develop engagement strategy	Activity: if I gave you raw data, which are the students you think could be in trouble? How do they envision that data from SIS could help them do their work? • Do you have access to students' data at SIS (what kind of data)? • Do you inspect students' data? – If yes: how often? What do you usually look for – If not: why not • What additional information could be meaningful? (stats about population per year, overall, historical data) [brainstorming]

<table>
<tr><th colspan="2">PART C: The Dashboard Duration: 30 minutes</th></tr>
<tr><td>Analyze internal capacity to change</td><td>Introduce the dashboard, show the assessments over the years and the visualizations
Can you find the students’ who are at risk and provide potential interventions?
How easy is it to review the information presented by the dashboard? (show only students’ at risk and skip the “safe”?) Does it provide you with the information you want?
The effectiveness of reasoning (wording, potential interpretations)? Is it helpful for you? Should this information focus on the actual metrics or should it provide pedagogical reasoning - for example, a student who might be registered in many courses in comparison to their classmates, might be overloaded and therefore at risk?
What about the model’s confidence for the assessments it provides? Would you like to have information about the model’s accuracy? How would it affect your practice?</td></tr>
<tr><td>Establish monitoring and learning frameworks</td><td>Ethical considerations
What are potential interventions? Let’s assume that these assessments are available to you and the model’s predictive accuracy is acceptable.
What would you do for the students who have a high risk of dropping out?
What would you do for the students who have a medium risk of dropping out?
Cost and efficiency: what would the additional cost of such interventions be for you [resources]?
What would be the potential dangers in case of an error? For example, a low-risk student who is predicted as high?</td></tr>
</table>

- After the focus group
  - Summary: summarize notes and ask for additional comments
  - Thank again, ask any questions, give contact details.