### SHEILA analytics Policy Framework v.1

This policy draft is based on the analysis of institutional interviews (n=64) using the ROMA framework. Four key elements are included in this policy framework, including action, challenges, and policy.

- **Action**: strategic action points to take in each step of the ROMA framework.
- **Challenges**: potential challenges that exist in each step of the ROMA framework. These challenges fall in categories that are organised alphabetically – capabilities, culture, infrastructure, management, methodology, ethics, and privacy.
- **Policy**: questions to guide the development of a policy that addresses the listed action points and challenges. These questions fall in categories that are organised alphabetically – data management, evaluation, methodology, policy management, purpose, and stakeholder engagement.

### Component 1 – Map political context

<table>
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<tr>
<th>ACTION</th>
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<tbody>
<tr>
<td>Identify internal and external drivers for learning analytics (e.g., problems to solve).</td>
<td><strong>Infrastructure</strong>&lt;br&gt;• Existing solutions in the market mainly focus on addressing retention problems.&lt;br&gt;• There is no one-size-fits-all model, even within one institution (different disciplines and learning modes).&lt;br&gt;<strong>Management</strong>&lt;br&gt;• Learning analytics competes with other institutional priorities.&lt;br&gt;<strong>Methodology</strong>&lt;br&gt;• Institutions feel pressured to adopt learning analytics even though the needs for it are unclear.&lt;br&gt;• Wrongly assume that learning analytics can provide all answers without having identified a question first (data driven approach).&lt;br&gt;• Learning analytics does not generate new insights into the understanding of learning or teaching.</td>
<td><strong>Purpose</strong>&lt;br&gt;• What are the reasons for adopting learning analytics?&lt;br&gt;• What are the questions to solve with learning analytics?</td>
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### Component 2 – Identify key stakeholders

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| • Identify primary users of learning analytics (e.g., students, teaching staff, and senior managers). | *Ethics & privacy*  
  - Marginalise hard-to-reach students by drawing a distinction between students who opt out and those who opt into a learning analytics service.  
  - The choice of opt-out or not opt-in could affect those who choose to opt in regarding the quality of data and services provided. | *Data management*  
  - How will consent be obtained?  
  - Is there an option to opt-out of any data collection and analysis?  
  - Who can access the data?  
  - Who owns the data?  
  - Will data be included in personally-identifiable formats?  
  - Can collected data be edited or deleted upon request? |
| • Identify senior management team to gain support (e.g., vice-chancellors, principals, provosts). | *Management*  
  - Define ownership and responsibilities among diverse professional groups within the university | |
| • Identify professional teams (e.g., IT, legal team, strategy team, Student Support, Student Registry, library). | *Privacy*  
  - Data sharing (particularly with third parties) requires a careful check of security issues and breaches of privacy. | |
| • Identify academic teams (e.g. Learning & Teaching committee, Digital Learning Committee, research project teams) | |
| • Identify external partners (e.g., researchers and service providers) | |
| • Identify internal advocates of learning analytics among members of faculties (bottom-up approach). | |

### Component 3 – Identify desired behaviour changes

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| • Identify areas where different stakeholders will be supported by learning analytics (macro level – institution, meso level – department/ programme, and micro level – teaching staff or students). | *Capabilities*  
  - Immature skills of interpreting data lead to wrong decisions.  
  - People mistrust the result of an analysis if the process is not transparent or if the analytical model is too complicated to understand. | *Methodology*  
  - How will transparency be achieved throughout a project cycle? |
| • Consider responsibilities and implications for all stakeholders. | *Ethics & privacy*  
  - Marginalise hard-to-reach students by drawing a distinction between students who opt out and those who opt into a learning analytics service.  
  - The choice of opt-out or not opt-in could affect those who choose to opt in regarding the quality of data and services provided. | *Purpose*  
  - What changes will learning analytics bring to the current situation?  
  - Why are these changes important to us? |
| • Consider inadvertent consequences. | | |
- Identify expected ‘changes’ to the current context.

**Management**
- Unethical profiling of students may occur when selecting those that are more likely to succeed.
- Students may be prone to choose subjects where they are likely to perform well.
- Users may game a LA system.
- Those who need support may not necessarily make use of information from learning analytics.

**Methodology**
- An experimental approach is susceptible to a sense of uncertainty in delivering the expected changes.

**Stakeholder engagement**
- What are the mechanisms to deal with inadvertent consequences?
- Who will benefit from learning analytics?
- How will the purpose of learning analytics be communicated to primary users?

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**Component 4 – Develop engagement strategy (*tends to iterate with step 5*)**

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<tr>
<td>Consult relevant policies and codes of practice (e.g., Jisc’s <em>Code of Practice for Learning Analytics</em>, and data protection policies)</td>
<td>Ethics &amp; privacy</td>
<td>Methodology</td>
</tr>
<tr>
<td>Align learning analytics with the wider institutional strategies or introduce learning analytics into the university’s strategy.</td>
<td>Learning analytics may induce fear and discomfort about surveillance.</td>
<td>What kinds of data will be collected to achieve these objectives?</td>
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<td>Seek funding.</td>
<td>Existing data protection regulations could restrict the way learning analytics is operated.</td>
<td>What is the scope of data collection?</td>
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<tr>
<td>Appoint specialists to lead learning analytics projects.</td>
<td>It is arguable to base predictive models on pre-determined factors, such as demographic characteristics.</td>
<td>What kinds of data will be presented? How? To whom?</td>
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<tr>
<td>Establish a working group and define a clear leadership structure.</td>
<td>Predictive models may result in unequal access to learning or support resources among students.</td>
<td>How should data be interpreted? Who will be involved in this process?</td>
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<td>Consider establishing an ethics commission.</td>
<td>Focus on students with a specific profile (e.g., struggling students, drop out risks) and ignore others.</td>
<td>How will resources be distributed efficiently and fairly as a result of the analysis of data?</td>
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<tr>
<td>Raise awareness through publicity and meetings/ workshops/ conferences.</td>
<td>Establish</td>
<td>Will there be interventions based on analytics? Who will decide the interventions?</td>
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**Establish**
- Consider phases of implementation (e.g., explore data, carry out pilot projects, seek feedback from users, and develop a policy for the adoption of learning analytics).
- Decide the scope of the project – the range of data.
- Choose analytical models and define metrics.
- Consider the best ways to present analytics results (e.g., visualisation).
- Select data that will be fed back to different stakeholders.
- Provide training for users.
- Consider providing a safe environment (e.g., a sandbox) for testing or research purposes.
- Decide forms of interventions (e.g., automatic systems, personal contacts, learning resources).
- Engage with research projects locally or through collaboration with other institutions.

### Component 5 – Analyse internal capacity to effect change

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<tr>
<td>• Evaluate risks.</td>
<td>• The maturity of data literacy varies among stakeholders and faculties.</td>
<td>• How will the data be stored and disposed?</td>
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<td>• Evaluate technological infrastructure.</td>
<td>• The lack of critical self-reflection skills reduces the chance to benefit from learning analytics.</td>
<td>• How often will the efficiency and security of existing data infrastructure be evaluated?</td>
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<td>• Establish indicators of data quality and system efficacy</td>
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<td>• Evaluate human capacity (e.g., data literacy, relevant expertise, staff workload, opportunities for skill transfer).</td>
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**Methodology**
- Overloading primary users with too many e-mails about analytics results.
- Strict data protection laws could hamper the adoption of learning analytics.

- Over rely on data and fail to consider the experience and knowledge of instructor/tutors about students.
- Leaving feedback loop unclosed (no follow-up support) leaves students in anxiety and potentially demotivates them.
- Focus on identifying students at risk and overlook the pedagogical design of curriculum or learning support.
- Peer comparison may demotivate students.
- Unsuccessful students may be discouraged by warning messages.

- Who will be affected by the interventions?
- Who will oversee ethical conducts related to learning analytics?

**Purpose**
- What are the objectives for learning analytics? How do they align with the institution’s vision for education?
- Will learning analytics be used as a management tool to monitor students as well as staff?
- Will learning analytics be used as a deficit model targeted at supporting students at risk of failure?
- Evaluate financial capacity.
- Evaluate existing legal framework and its applicability for learning analytics.
- Evaluate institutional culture (e.g., trust in data and openness to changes and innovation).
- Evaluate resources available for primary users to uptake learning analytics (e.g., ownership of mobile devices).

- The understanding/interpretation of data protection regulations vary among legal officers, researchers, and teaching staff.
- Digital capabilities affect the desire to opt into a learning analytics service.
- Limited awareness or discussion regarding privacy and ethical issues cripple the adoption of learning analytics when issues arise.

**Culture**
- Institution-wide buy-in is hard to reach.
- Instructors are more interested in establishing a research profile than enhancing teaching and learning.
- Senior managers are more interested in financial benefits to the institution than the benefits in enhancing learning and teaching.
- There is unequal engagement/interest in learning analytics among primary users (e.g., differences in gender, age, and disciplines influence the degree of interest).
- There is no common understanding of learning analytics among stakeholders at different levels (e.g., managers, teaching staff, IT officers, and students).
- Concerns about data protection hinder buy-in.
- Reluctance to change is present among some teaching staff (e.g., try new or unfamiliar technologies, or change teaching styles).
- Training could be difficult to deliver when staff lack time.

**Infrastructure**
- Some useful data remains inaccessible.

- How will data integrity be achieved?
- Is there an application procedure for using learning analytics for research or teaching purposes? Are the procedures different?

**Policy management**
- Are there related policies in the university that the policy sits alongside/above/below?
- Are there any national/international policies that this policy has to adhere to?
- What mechanisms will be used to communicate the policy effectively to stakeholders?

**Stakeholder engagement**
- What training will be deployed to scale up data literacy and incorporate learning analytics into daily practice? Will the training be compulsory for any stakeholder?
- What communication channels or feedback mechanisms will be in place?
- Will learning analytics exclude certain groups of students? Will there be mechanisms to address inequality?
- How will the current policy be communicated to different stakeholders?
Data is held in silos.
- Data is fragmented.
- Data is noisy.
- Setting up a learning analytics environment is costly.

Management
- 2018 GDPR requires changes in existing practice and system (e.g., coping with individual opt-outs).
- Central steering groups and individual project groups do not coordinate.
- Engaging students with institutional policies in an informed way.

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<th>Component 6 – Establish monitoring and learning frameworks</th>
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<tr>
<td>- Set up measurable milestones.</td>
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<td>- Establish qualitative and quantitative indicators of success.</td>
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<td>- Seek feedback from primary users through various channels.</td>
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<td>- Develop methods to triangulate analytics results.</td>
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