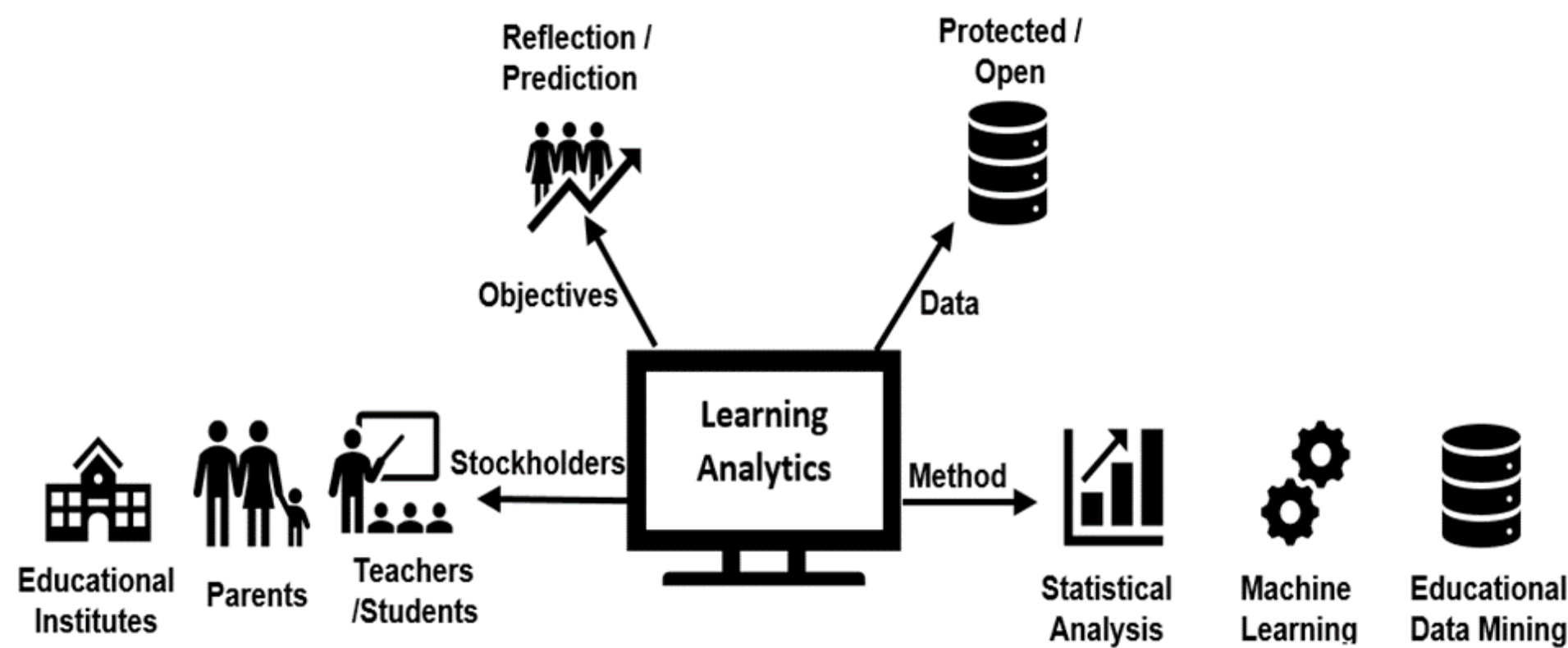


Introduction

Motivation has been considered as a significant factor in students' academic journeys. This is supported by many learning theories such as self-regulated which highlights the importance of motivation for achievement and learning (Boekaerts 1999; Pintrich 2000; Schunk et al. 2008; Zimmerman 2002). In fact, the availability of a vast amount of educational data lead to changes in learning and learning environment (Long & Siemens, 2011). Learning analytics are the main reason for the increase of educational data usage.

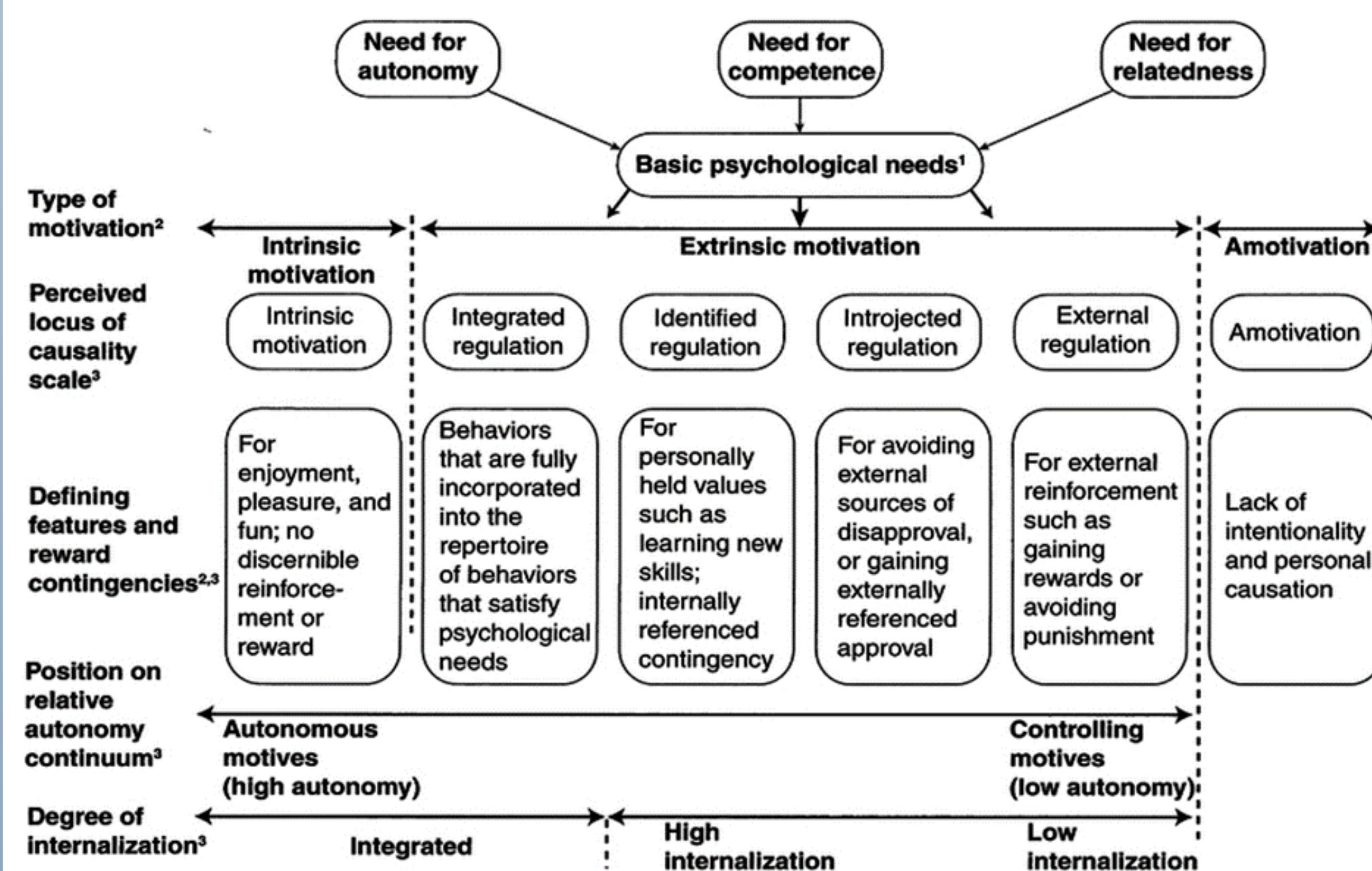


Problem Statement

Student motivation has not yet been investigated in learning analytics context (Schumacher & Ifenthaler, 2018). In learning, motivation plays a significant role. However, most of current research on learning analytics focus on data privacy, data processing and developing user systems. But connecting learning analytics with the learning theory and students' motivation is still on its infancy phase.

Background Information

■ Motivation in Education (Self-Determination) Theory



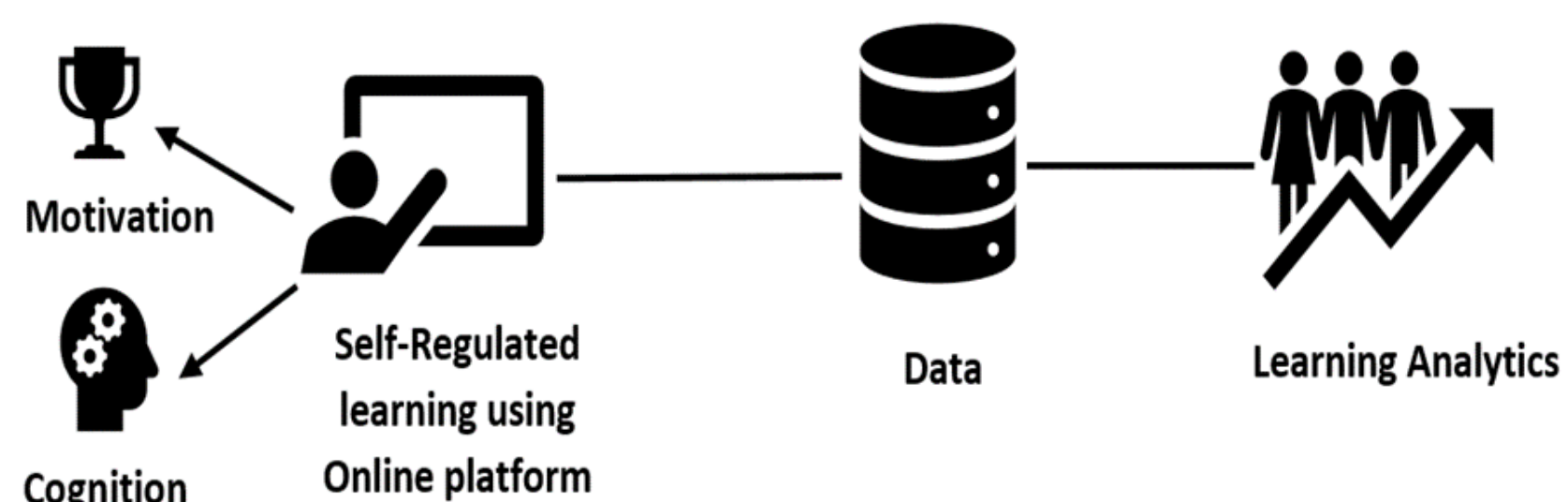
Self-Determination continuum based on Deci and Ryan (1985)

■ Assessing Motivation

- 1) Academic Motivation Scale (AMS) by Vallerand et al., (1992)
- 2) Basic Needs Satisfaction in General Scale developed by Gagné (2003)

■ Learning Design and Learning Analytics

■ Self-Regulated Learning (SRL), Motivation and Learning Analytics



Self-Regulated learning and Learning Analytics

Aim / Objectives

Aim

- Discovering the motivational factors that affect computer science students using learning analytics techniques.

Objectives

- ✓ Using mixed method approaches to identify computer science students motivational and engagement factors.
- ✓ Using Thematic analysis to produce a theoretical framework that represents computer science students' motivational factors
- ✓ Using Structure Equation Modelling to test the connection between the identified factors.

Methodology

A mixed method will be used which uses more than one phase of data collection and analysis. In this context, a triangulation of data (Flick, 2004) is used to combine a collection of data from different sources such as interviews, surveys, questionnaires etc.

In the first stage, we will target students undertaking a data analytics course at the University of Huddersfield. The Academic Motivation Scale and Basic Needs Satisfaction scale will be distributed as a survey for the targeted sample. The survey will collect information about each individual motivation category and learners' basic needs identification. The survey result will then be matched with students' learning analytics data records. A semi-structure interview will be performed to get in-depth understanding of the survey result

In the second stage, to generalize and expand the result of our first stage. We would use a wide range survey that will target computer science students.

Phase	Procedure	Product
Qualitative data collection	<ul style="list-style-type: none"> • Survey • Semi-structured interview 	<ul style="list-style-type: none"> • Qualitative data
Qualitative data analysis	<ul style="list-style-type: none"> • Thematic analysis 	<ul style="list-style-type: none"> • Visual model • Codes and themes
Connecting qualitative and quantitative phase	<ul style="list-style-type: none"> • Selecting the sample • Develop new survey based on the sample from first survey 	
Quantitative data collection	<ul style="list-style-type: none"> • Survey 	<ul style="list-style-type: none"> • Quantitative data
Quantitative data analysis	<ul style="list-style-type: none"> • Structure equation modelling • Internal consistency 	<ul style="list-style-type: none"> • Model with variables connection
Integration of quantitative and qualitative result	<ul style="list-style-type: none"> • Interpretation and explanation of the result from qualitative and quantitative phase 	<ul style="list-style-type: none"> • Discussion • Implication • Future research

visual model of the sequential exploratory design

Ethics and Privacy

There are different ethical issues need to be addressed in learning analytics related to student data privacy.

- General Data Protection Regulation (Calder, 2016).
- Data privacy regulations (Lane et al., 2014).

Conclusion

Learning Analytics interpretations are developed to optimize student learning experience and the context in which they can learn more effectively. The study presented here is explaining the framework of how LA can be used to understand computer science student motivation and therefore help them to enhance their learning process. The result of this study will help student on their academic achievement and motivation which will result in making better decision about their study.

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