# Investigating the Role of Professional Self-Efficacy as Mediator between Teacher Self-Efficacy and Learning Analytics Use in Schools

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***Abstract*—Learning analytics adoption in educational institutions at all levels is increasing over time. Teachers have realized educational data could be valuable and beneficial when properly collected, analyzed, and interpreted. Despite previous research that has confirmed the importance of teacher self-efficacy and learning analytics use, a holistic process model including these relationships has been primarily conceptual rather than empirical. This study draws on the Social Cognitive Theory, emphasizing the direct and indirect relationships between teacher's self-efficacy on the utilization of learning analytics. Using data provided by the Ministry of Education Malaysia, a random sampling technique was employed to choose 384 primary and secondary school teachers to complete a set of questionnaires. Structural equation modelling was performed to test the model. Results revealed that teachers' usage of learning analytics was at a moderate level, while further analysis indicated that teacher self-efficacy was positively related to learning analytics concurrently. Professional self-efficacy was found to mediate the relationships between data use self-efficacy, technology use self-efficacy and learning analytics use. These findings implicate that collaborative efforts among stakeholders, researchers, and policymakers are key to guaranteeing conducive working conditions that promote teacher's use of learning analytics in the profession. The substantial use of learning analytics by Malaysian school teachers is driven by their belief in its effectiveness, supported by self-efficacy in technology, which collectively contributes to successful learning analytics adoption and a higher understanding of technology use in education.**

***Keywords*—learning analytics, self-efficacy, technology use, data use**

## I. Introduction

Today's world has advanced to the Fourth Level of Industrial Evolution (IR4.0), and with the advancement of technology, teaching and learning have shifted from the traditional face-to-face approach to a blended approach, utilizing electronic, digital, and online platforms. This transformation has brought challenges for teachers in measuring, assessing, and making decisions about student learning and performance. To address the issues facing the educational system, newly improved technology must be adopted.

Over the past decade, a massive volume of educational data has been generated from adopting educational technologies such as online learning platforms, virtual classrooms, online information systems, and gamification. Educational data present information and knowledge about instructional and learning practices such as students' online traces, log-in frequencies, hours spent, number of accessed learning resources, test results, and views number [1]. Using data analytics, educational data can be manipulated to support effective decision-making, scaffold and improve student learning outcomes, and ensure better education quality [2]. Undeniably, teachers need to have high and steady self-efficacy to be able to use data-related educational technologies efficiently and effectively. Hence, teachers must possess the necessary analytics competencies and skills to promote effective teaching [3].

There is undivided attention to educational research and projects regarding the potential and roles of data analytics to leverage educational data for teaching and learning improvement. Such endeavors have led to the emergence of a new education field, Learning Analytics (LA). LA focuses on measuring, collecting, analyzing, and reporting data to improve students' learning and optimize the surrounding environments [4]. According to Chatti *et al.* [5], LA revolves around the type of data, source of data, type of analytics, educational goals, and analytics approach.

Educational systems often implement technological changes to enhance quality and performance, but these can pose significant challenges for teachers, potentially decreasing their performance and professional self-efficacy, with limited research on the impact of such demands [6]. Current studies suggest a link between teacher self-efficacy and factors such as job satisfaction [7, 8], stress management [9], burnout [10], and technology acceptance [11]. Yet, the specific impact of technology and data use on teachers' professional self-efficacy remains underexplored, representing a critical gap in understanding the broader effects of digitalization on teacher well-being and effectiveness.

This study advances the field of educational technology by offering valuable insights into the implementation of LA in schools, particularly focusing on the impact of self-efficacy factors related to LA, such as technology use, data use, and professional self-efficacy. While previous research has largely concentrated on the design and development of LA technologies, often using experimental designs, few studies have explored the factors influencing LA adoption. In this context, the current study contributes by empirically examining the relationships and effects between LA use and various self-efficacy variables within school environments,

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addressing a gap in understanding the practical influences of LA integration in education. Therefore, this study aims to empirically improve insight and expand understanding of the relationships between TSE (professional, technology use, and data use) and LA use in the classroom. This study seeks to confirm several assumptions by achieving the following research objectives:

1) To determine the level of teachers' learning analytics use;
2) To examine the influence of teachers' self-efficacy on the learning analytics use;
3) To examine the role of professional self-efficacy as a mediator between technology use self-efficacy, data use self-efficacy, and learning analytics use.

The following hypotheses are developed and investigated to achieve research objectives 2 and 3:

1) Data use self-efficacy has a significant influence on professional self-efficacy.
2) Technology use self-efficacy has a significant influence on professional self-efficacy.
3) Data use self-efficacy has a significant influence on learning analytics use.
4) Technology use self-efficacy has a significant influence on learning analytics use.
5) Professional self-efficacy has a significant influence on learning analytics use.
6) Professional self-efficacy mediates the influence of data use on learning analytics use.
7) Professional self-efficacy mediates the influence of technology use self-efficacy on learning analytics use.

## II. Literature Review

### A. *Learning Analytics Use*

Implementing LA is not an unfamiliar practice in educational institutions. The use of LA to guide and support teaching and learning has yet to reach widespread adoption. Nonetheless, LA adoption awareness and readiness in educational institutions teachers have increased over time [12]. Teachers have realized that educational data could be precious and beneficial when properly collected, analyzed, and interpreted. Effective intervention can be made from learning analytics aligned with learning outcomes and could bring more advantages in providing timely feedback, improving performance, and increasing achievement [13]. To warrant effective implementation of LA, teachers must use educational data best, integrate data analytics into their day-to-day activities, and nurture a cultural change in educational practices.

Teachers utilize data to gain insights into students' learning, particularly in assessing academic performance, evaluating learning achievements, and preparing detailed reports on educational progress [14]. While this traditional data use is essential, advanced technologies that incorporate sophisticated data processing techniques, such as those used in LA, are more effective in managing and analyzing the vast amounts of data generated by online learning platforms and digital tools. These technologies offer a more efficient way to process and interpret complex educational data, providing deeper insights into student learning patterns and outcomes [12].

Research in LA use has been found to significantly influence practical instruction activities and improve learning. Evidence from research supports the claim that LA has improved students' performance in schools. For example, Carlson *et al*. [15] manifested a significant rise in mathematics performance and notable reading improvement after data-driven reform in one year. In a mixed methods research, Bernhardt [16] inferred that LA is perceived as needed by students and parents to reform strategies and behaviors and to influence student performance.

Another study showed that using an LA tool such teacher-alerting dashboard indicated that students' science inquiry performance has improved [17]. The study shows that real-time alerts were effective in helping teachers respond to student science inquiry difficulties and, correspondingly, promoted student improvement in science practices. Moreover, using computer-based collaborative reading and an LA environment has pointed to several potentialities, including fostering self-awareness, reflective and self-regulatory learning dispositions, improving learning motivation and engagement, and supporting connective literacy among students [18].

It is concluded that adopting and using LA in educational settings is beneficial for teaching and learning improvement. In this study, LA use is defined as teachers' perception of their frequency of using LA in the classroom for purposes such as identifying learning needs, discussing data and progress, setting goals, etc.

### B. *Teacher Self-Efficacy*

Self-efficacy is one of the essential motivational keys for effective teaching and learning in school. Self-efficacy has a direct strong relationship to certain aspects of instructional quality and has shaped performance, achievement, and motivation [10]. According to Bandura's social-cognitive theory, "human functioning involves a dynamic interplay of intrapersonal, behavioral, and environmental factors" [19]. It is proposed that self-efficacy should be measured effectively within a specific domain by evaluating abilities and proficiencies across different situations and conditions at different levels of complexity within the environment [20]. In general, the higher the self-efficacy the human has, the better the performance at their job, and they have been observed to have more perseverance, determination, and less stress [20].

In the teaching domain, Teacher's Self-Efficacy (TSE) is defined as "teachers' beliefs in their capabilities to teach and to accomplish desired outcomes of student engagement and learning" [10]. Indeed, studies showed that TSE is related to several relevant factors affecting teacher performance, like student academic performance, motivation, and instructional quality [10]. Teachers with higher self-efficacy beliefs about themselves spend longer time in planning, exhibit greater motivation for teaching, are more accepting of contemporary ideas and methods, are better organized and planned, and stayed to be more insistent in working with struggling and problematic students [21]. Therefore, teachers with LA skills and knowledge contribute to increased self-efficacy and confidence. Confident teachers are more likely to take risks, try new approaches, and adapt to the evolving needs of their students.

TSE has been studied in particular fields, such as learning, teaching, and social [22]. For instance, computer self-efficacy is a generic sense of self-efficacy and represents the fundamental elements applied in computer use literacy and skills [23]. Training in computers and their utilization may be relevant to the increased efficacy beliefs about computer use, which may influence the increased motivation to use technology [24]. In this paper, TSE contributes to self-efficacy literature by examining the relationship among the three domains: 1—professional, 2—technology use, and 3—data use associated with teachers' use of LA in teaching and learning environments.

*1) Professional self-efficacy*

In particular, the professional self-efficacy domain, or occupational self-efficacy, has become the center of attention by many researchers [25]. Professional self-efficacy is a unique one in the occupational domain. Workers' beliefs and confidence about their capabilities to perform job tasks effectively are highly associated with their beliefs about their abilities to plan, organize and carry out the courses required to perform specific actions better [19]. Professional self-efficacy is not an individualized personality attribute or job characteristic. Instead, it is the belief or confidence in performing work with specific capabilities. Some researchers have considered professional self-efficacy a generic and not a particular domain of self-efficacy [22].

Generally, the previous study on professional self-efficacy involves two facets: 1) self-efficacy associated with work content or worker self-belief in completing the specific content. For example, the level of education a professional needs or the skills and competencies required to carry out a particular work task; 2) self-efficacy is associated with the process of job behavior that a worker believes he can. For example, job decision-making, job-seeking, and behavioral targets achievement [26]. In many studies, professional self-efficacy was evaluated by assessing participants' belief in their competencies and proficiencies to accomplish what are perceived to be the primary work requirements [22].

Teachers' professional self-efficacy is a critical issue in education that significantly impacts instructional quality, student engagement, and overall classroom outcomes [21]. Despite its importance, there is a notable gap in understanding the specific challenges and factors influencing teachers' occupational self-efficacy. This knowledge deficit hinders the development of targeted interventions and support systems aimed at fostering and sustaining high levels of self-efficacy among teachers, thereby compromising the quality of education and potentially contributing to teacher burnout and attrition.

Professional self-efficacy was found to mediate the relationship between occupational factors such as job satisfaction and career calling, and between in-role performance and career calling [22], work performance and work motivation [26], job insecurity and job-related learning [25]. Consequently, this study hypothesizes that professional self-efficacy might have significant mediation roles in technology use self-efficacy, data use self-efficacy, and learning analytics use.

*2) Technology use self-efficacy*

The influence of technology is continuously improving in the education process. Teachers with knowledge of information technology and competencies to take advantage of technology in classroom activities have achieved more intentions in the 21st century. The International Society for Technology Education (ISTE) characterizes technology use among teachers as encompassing several key abilities. These include being technologically literate, organizing learning environments conducive to student technology use, guiding students in utilizing technology effectively, facilitating access to information, fostering online collaboration with colleagues for professional development, and sharing experiences within the educational community [27].

Technology use self-efficacy can be defined as one's own belief about the use of tools and instruments for "creating, gathering, processing, re-obtainment, distribution, conversion and evaluation processes of the information in an educational environment or his realization efficacy of making them coherent to these environments" [28]. Technological self-efficacy was acknowledged as the dominant factor regarding the intention of technology usage [29]. Teachers with high self-efficacy in technology use exhibit a range of advantages, including the effective integration of technology into their lessons, increased student engagement through diverse digital resources, improved instructional quality with multimedia-rich content, efficient classroom management, and enhanced personalized learning opportunities [30]. Overall, high self-efficacy in technology enables teachers to adapt to educational trends, fostering a dynamic and effective teaching environment.

Apart from technology acceptance, technology se self-efficacy has been viewed as the most favorable individual domain in demonstrating that technology influences outcomes. Research reported a positive association between self-efficacy and technology use experience [31]. Technology use self-efficacy is among the significant factors to measure associations and the influences of technology use and acceptance in the education system. For example, research showed that self-efficacy predicted not only computer course enrollment but also the experience and usage of electronic technologies [24]. When examining the utilization of learning technology in education, Raines and Clark [32] concluded that students understand teachers relatively better when technology is being used in class.

Thus, technology use self-efficacy is one of the factors that should be focused on in the process of learning analytics implementation. Studies have shown that individuals with high self-efficacy in technology use are more likely to have positive attitudes towards technology-based learning and are more motivated to engage in self-directed learning [6]. This study hypothesizes that technology use might have significant influences on professional self-efficacy and learning analytics use.

In this study, technology use self-efficacy is defined as teachers' belief in their skills and competencies to use technology-related tools and platforms to conduct learning analytics to accomplish intended learning outcomes.

*3) Data use self-efficacy*

Teachers' data use self-efficacy, as defined by Dunn *et al*. [33], encompasses their confidence in successfully undertaking activities related to data utilization to enhance student performance. This involves the complete data use process, including collection, analysis, and interpretation, with the ultimate goal of gaining valuable insights into educational practices. When teachers use data as a foundation for decision-making related to academic courses and technology adoption, it has been associated with improved learning outcomes, as noted by Coburn and Turner [34]. By integrating data-informed decision-making into their instructional strategies, teachers can identify areas for improvement, tailor their teaching approaches to individual student needs, and make informed choices about the integration of technology, ultimately contributing to more effective and targeted educational practices.

The concept of data use self-efficacy among teachers underscores the importance of their confidence and competence in handling data-related tasks, including statistics, organization, and technology. As highlighted by Dunn *et al.* [33], teachers may face discouraging barriers when implementing data analytics practices, particularly on a large scale, due to limited knowledge and competency in these areas. The shortfalls in teachers' understanding of data statistics, organization, and technology, coupled with low confidence levels, can hinder the successful adoption of data-informed decision-making processes.

Sun *et al*. [35] emphasize that teachers often lack the essential competencies to comprehend, interpret, and analyze data effectively. This deficiency in skills may impede their ability to make informed educational decisions based on data insights and address any weaknesses identified through data analysis. Therefore, addressing these competency gaps and fostering teachers' confidence in data use is crucial for the successful implementation of data analytics practices in education.

Numerous studies have indicated a positive association between the use of student learning data and various measures of student performance and school improvement [36]. Furthermore, research has confirmed that teachers' dispositions, attitudes toward data, mindsets, and efficacy play a crucial role in shaping their implementation of data-based practices [37]. The implementation of a data-use inquiry process by teachers becomes instrumental in this context [38]. Participation in such a process is anticipated to influence teachers' self-efficacy, beliefs, and confidence in utilizing data effectively.

Engaging in the LA not only contributes to improved educational decision-making but also has the potential to positively impact teachers' perceptions and attitudes toward data use. Consequently, this study hypothesizes that data use might have significant influences on professional self-efficacy and learning analytics use.

Data use self-efficacy is defined as teachers' confidence in their competencies in leveraging various educational data to guide instructional behaviors with the aim of achieving desired learning outcomes for students. This definition underscores the importance of teachers' confidence and perceived capabilities in effectively utilizing diverse forms of educational data for instructional decision-making. Focusing on data use self-efficacy becomes essential for ensuring that teachers not only possess the necessary technical skills but also feel empowered to apply their knowledge in a manner that positively influences students' learning outcomes. Acknowledging and addressing teachers' self-efficacy in data use can contribute to the successful integration of LA into educational practices, fostering a more informed and effective teaching environment.

## III. Methods

### *A. Research Method*

This study employed a correlational quantitative design, using a survey method for data collection. The survey approach was chosen as it allows for gathering data from a large sample, offering a more comprehensive representation of the population [39]. The research aimed to examine how teachers' self-efficacy in technology use, data use, and professional competence influence the implementation of learning analytics in schools. The questionnaire and methodology received approval from the Educational Policy Planning and Research Section, Ministry of Education Malaysia (ERAS), with the ethics approval number KPM.600-3/2/3-eras[20378]. Additionally, informed consent was obtained from all participants before their involvement in the study.

### *B. Population and Sampling*

Teachers from public national schools in Malaysia, both primary and secondary, made up the population of the study. The population was 416,743 according to Ministry of Education Malaysia in 2021. To ensure the sample represents the broader population accurately, national, primary, and secondary schools were included, with certain types excluded. Fully residential, technical, religious, premier, special education, special model, international, and private schools were omitted due to their unique contexts, student demographics, and instructional approaches differing from public school settings.

According to Raosoft's sample size calculator, a minimum of 384 respondents is required to achieve a 95% confidence level, ensuring that the surveyed value falls within ±5% of the true population value. Only one respondent was selected from one school. Therefore, 384 schools were selected to represent the sample. The selection of schools was carried out through a random sampling technique, employing Furey's online random number generator for the process. Furey's generator produced 385 random numbers from a pool of 10,220 schools in Malaysia. Each number matches a school's position in the list downloaded from the Ministry of Education Malaysia website as of 2023, identifying the specific schools to include in the sample. Respondents who did not complete the survey (due to lack of internet access, unread emails, etc.) were replaced by respondents from other schools.

### *C. Data Collection*

Data were collected randomly. Selected teachers were emailed the Google Form access link. The survey consists of three sections: Section A: School Teacher's Demographic Information, Section B: Analytics Use, and Section C: Teacher Self-Efficacy (Professional, Technology Use, and Data Use)

First, the researcher obtained approval from the UPM Ethic Committee to involve human subjects in data collection. The researcher also sought approval from the Educational Planning and Research Department to conduct surveys in schools. After receiving approvals from JKEUPM and EPRD, permission to conduct was also obtained from the Departments of State Education and Departments of District Education.

After receiving approvals from the agencies above, emails containing the invitation letter were sent to all selected schools. The school administrator distributed the questionnaire's Quick Response (QR) Code/link to the chosen teachers. The teachers then completed the survey utilizing mobile devices such as smartphones, tablets, and laptops. The questionnaire responses were automatically recorded and downloaded as *.csv files from the Google Form account for analysis. The responses to the teachers' questionnaire were automatically documented and forwarded to the researcher using the Google Forms application.

### *D. Measurement and Instrumentation*

The LA use variable was measured using the 8-item analytics use (Table 1) developed based on the data use instrument [36]. The items measure analytics using a five-point Likert scale: 1—Never; 2—Seldom; 3—Sometimes; 4—Frequent; 5—Very Frequent. A high score indicates a high level of analytics use by teachers. TSE was measured using three (3) dimensions: professional, technology use, and data use. The items were based on a five-point Likert agreement scale: 1—Strongly Disagree; 2—Disagree; 3—Undecided; 4—Agree; 5—Strongly Agree.

Table 1. Learning analytics use items

| Item | Statements |
|---|---|
| | I use learning analytics to: |
| 1 | "Identify learning needs of students." |
| 2 | "Discuss student progress or instructional strategies with other teachers." |
| 3 | "Tailor instruction to individual student needs" |
| 4 | "Identify instructional content to use in class." |
| 5 | "Set learning goals for individual students" |
| 6 | "Assign or reassign students to classes or groups." |
| 7 | "Discuss data with a parent or student." |
| 8 | "Interact with your principal about data use." |

Table 2. Teacher self-efficacy items

| Variables | Statements |
|---|---|
| Professional Self-Efficacy | "I can work effectively." |
| | "I am satisfied with the quality of my work." |
| | "I feel that I am being successful in my work." |
| | "I have sufficient self-confidence to defend my points of view about the work." |
| Technology Use Self-Efficacy | "I am confident I can use technology to retrieve and save data." |
| | "I am confident I can use technology to manage student learning online or offline." |
| | "I am confident I can use technology to measure and evaluate student learning." |
| | "I am confident I can use technology to create reports and presentations (e.g., create documents, charts, tables, graphs, etc.)." |
| Data Use Self-Efficacy | "I am confident I can use data to identify students' learning needs." |
| | "I am confident I can use data to identify gaps in teaching and learning practices." |
| | "I am confident I can use data to provide feedback about learning performance or progress." |
| | "I am confident that I can use data to provide interventions for teaching and learning." |

Professional self-efficacy consists of 4 items (Table 2) adapted from the sense of self-efficacy instrument [40]. The instrument measures the extent to which teachers feel a sense of self-efficacy beliefs regarding their profession. Technology and data use self-efficacy consists of 8 items (Table 2) adapted from the data-based decision-making efficacy instrument [33]. The device measures the use of data and technology in the classroom. The instrument reveals academic performance through accomplished learning goals and the planning of instructional practices to scaffold academic performance.

Cronbach's Alpha was used to obtain the reliability index of each construct in the research instrument. Table 3 shows the Cronbach's alpha coefficient, which ranges between 0.838 and 0.922. All values are higher than 0.70 [41], indicating that the instruments are suitable for use in the actual study. The inter-item correlation mean value above 0.25 also indicates that the construct is valid for pilot studies [41]. The item correlation mean ranges from 0.530 to 0.747 in Table 3, confirming that the research instrument is valid and can measure the constructs well. To check whether a data set is distributed normally, two statistical numerical measures of shape—skewness and excess kurtosis—are used. Data is assumed to be expected if the skewness value is between −2 to +2 and kurtosis is between −7 to +7 [42].

Table 3. Constructs validity, reliability, and normality

| Variables | Cronbach's Alpha | Inter-Item Correlation Mean | Skewness | Kurtosis |
|---|---|---|---|---|
| Analytics Use | 0.898 | 0.530 | −0.275 | 0.202 |
| Professional SE | 0.838 | 0.564 | −0.385 | 0.503 |
| Technology Use SE | 0.895 | 0.681 | −0.250 | 0.850 |
| Data Use SE | 0.922 | 0.747 | −0.372 | 0.085 |

### *E. Research Framework*

The research framework is shown in Fig. 1. The study statistically measured four constructs of the study: technology use self-efficacy, data use self-efficacy, professional self-efficacy, and learning analytics use. The measurement used Structural Equation Modelling (SEM) as the statistical analysis tool and professional self-efficacy as a mediating construct using bootstrap test analysis.

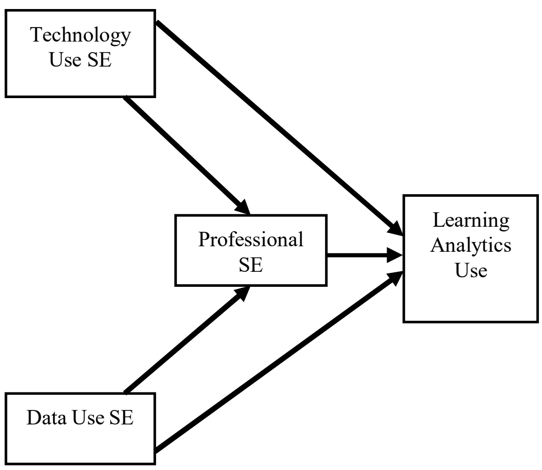


Fig. 1. Research framework.

Technology use self-efficacy refers to teachers' confidence in utilizing technological tools in educational settings, while data use self-efficacy is linked to teachers' ability to interpret and apply data insights to inform instructional practices. Both of these self-efficacy types are presented as foundational, indicating that they play a crucial role in shaping overall professional self-efficacy. By placing these two elements as prerequisites for professional self-efficacy, the model implies that specific skills in technology and data handling strengthen teachers' general professional confidence.

Professional self-efficacy is also an essential component of the research framework. This part of the tool focuses on teachers' confidence in employing both data and technology effectively to enhance instructional practices. Together, these components provide a comprehensive picture of how data and technology integration support academic performance by tracking learning goals and guiding instructional planning aimed at promoting student success.

Professional self-efficacy acts as a mediating factor in this framework, linking the specific competencies in technology and data use with LA Use. This suggests that while skills in technology and data are important, they must translate into a broader sense of professional confidence to effectively influence engagement with learning analytics. Essentially, professional self-efficacy represents teachers' overall belief in their capability to fulfil their roles successfully, and it encompasses more than just technical skills. Therefore, this framework highlights the idea that a solid foundation in data and technology not only enhances specific skills but also builds a stronger, more general sense of competence, which is essential for leveraging learning analytics.

The ultimate focus of the framework is LA use, positioned as the outcome variable that is directly influenced by professional self-efficacy. This placement suggests that teachers who feel confident in their professional abilities, supported by their skills in technology and data, are more likely to engage with and utilize LA in their teaching. This engagement could be critical in making data-driven decisions to enhance student learning and outcomes. By understanding how these types of self-efficacy are interrelated, researchers can design targeted interventions to improve educators' readiness to work with learning analytics, thereby encouraging more effective data-informed instructional practices. This framework, therefore, offers a structured approach to exploring how building self-efficacy in technology and data can lead to greater integration of LA in educational environments.

The measurement of LA use was conducted using an 8-item scale that draws from an established data use instrument [36]. This scale, outlined in Table 1, provides a structured approach to evaluating the extent to which individuals utilize LA. By measuring LA use, this tool allows researchers to assess how data-driven insights are integrated into instructional decisions, helping to illuminate areas where analytics contribute to learning outcomes and areas that may benefit from further training or resources.

### *F. Analysis*

All test analysis was conducted using the SPSS 26.0. The confirmatory factor analysis (CFA) was run and measured using AMOS 26.0. The bootstrap test was performed to measure mediating effects, and $P < 0.05$ was considered statistically significant. According to Hair *et al.* [42], a model was supposed to have reasonable goodness fit if relative chi-square ($\chi^2$) <= 5.0, root mean square error of approximation (RMSEA) < 0.08, and one or two of appropriate indices (GFI/AGFI/IFI/CFI/NFI/TLI) > 0.90.

## IV. RESULT

### *A. Descriptive Analysis*

A total of 384 teachers completed the study. Female (62%) comprised the majority percentage of the respondents compared to male (38%), and most of the teachers (77.9%) are between the ages of 30 and 49 years old. Most respondents also serve in primary schools (62.5%) and rural schools (62.5%).

Additionally, the result of descriptive analysis for the analytics used in descending order is shown in Table 4. Based on the development, the most frequent use of learning analytics by teachers in school is to identify instructional content (Item 4), followed by learning goal setting (Item 5), and to tailor instruction for individual needs (Item 3). The least frequent use of analytics is for parental and management discussions. The mean value ranges from 3.00 (sometimes) to 4.00 (regular), indicating moderate teacher use of analytics in school.

Table 4. Analytics use descriptive analysis

| Item | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| 4 | 384 | 2.00 | 5.00 | 4.0552 | 0.72759 |
| 5 | 384 | 2.00 | 5.00 | 3.9105 | 0.73981 |
| 3 | 384 | 2.00 | 5.00 | 3.8895 | 0.74341 |
| 1 | 384 | 1.00 | 5.00 | 3.8667 | 0.75243 |
| 2 | 384 | 1.00 | 5.00 | 3.8400 | 0.76985 |
| 6 | 384 | 1.00 | 5.00 | 3.8210 | 0.75307 |
| 8 | 384 | 1.00 | 5.00 | 3.7010 | 0.81966 |
| 7 | 384 | 1.00 | 5.00 | 3.3048 | 0.87068 |

### *B. Confirmatory Factor Analysis (CFA)*

As a result of the analysis, the model's fit for individual variables (single-factor model) was determined as in Table 5. Considering the data acquired, it was observed that the fair values of the model were acceptable without modification except for Analytics Use, where item 7 was deleted, and for Technology Use SE, where item 4 was dropped from the model. All other items' factor loading was observed to be more than 0.5, positive, and not more than 1.0, indicating that the goodness of fit is attained [43]. Convergent validity refers to a set of indicators that presume to measure a construct [44]. Average Variance Extracted (AVE) values > 0.5 indicate a high convergent validity. Meanwhile, construct reliability (CR) is comparable to Cronbach alpha. The instrument with CR > 0.70 is considered reliable [42].

Table 5. Fit indices, AVE, and CR

| Variables | Relative $\chi^2$ | RMSEA | GFI/AGFI/IFI/CFI/NFI/TLI | AVE | CR |
|---|---|---|---|---|---|
| Analytics Use | 3.894 | 0.074 | All > 0.9 | 0.550 | 0.894 |
| Professional SE | 0.662 | 0.000 | All > 0.9 | 0.568 | 0.839 |
| Technology Use SE | 1.195 | 0.019 | All > 0.9 | 0.691 | 0.869 |
| Data Use SE | 2.962 | 0.061 | All > 0.9 | 0.738 | 0.919 |

### C. Measurement Model

All individual variables were correlated to each other to build a measurement model. As a result of the analysis, it was observed that all items factor loading > 0.5. Relative chi-square ($\chi^2$) = 2.794, root mean square error of approximation (RMSEA) < 0.059, and one or more (GFI/AGFI/CFI/NFI/TLI) > 0.90. The goodness of fit of the model was found acceptable without modification.

Table 6. Discriminant validity

| Variables | CR | Analytics Use | Professional SE | Technology Use SE | Data Use SE |
|---|---|---|---|---|---|
| Analytics Use | 0.897 | 0.557* | | | |
| Professional SE | 0.841 | 0.298** | 0.570* | | |
| Technology Use SE | 0.922 | 0.334** | 0.411** | 0.747* | |
| Data Use SE | 0.870 | 0.325** | 0.358** | 0.599** | 0.692* |

*AVE; **correlation squared ($r2$)

A discriminant validity test was performed to confirm the extent to which a variable is genuinely discriminated from other constructs. Discriminant validity involves an association between a specific latent construct and other constructs of a similar nature [45], where all constructs are assumed to be genuinely distinct from others. The AVEs for the two interrelated variables must be greater than their $r^2$ [43]. Table 6 demonstrated that analytics use, professional use self-efficacy, technology use self-efficacy, and data use self-efficacy exhibit sufficient discriminant validity.

### D. Structural Model

Exogenous and endogenous variables were identified based on the study's conceptual framework to build the structural model (Fig. 2). The structural model represents a set of one or more dependence relationships linking the hypothesized model's variables. The model helps describe the interconnections between exogenous and endogenous constructs. As a result of the analysis, it was observed that all items factor loading > 0.5. Relative chi-square ($\chi^2$) = 2.794, root mean square error of approximation (RMSEA) < 0.059, and one or more (GFI/AGFI/CFI/NFI/TLI) > 0.90. The goodness of fit of the structural model was found acceptable without modification.

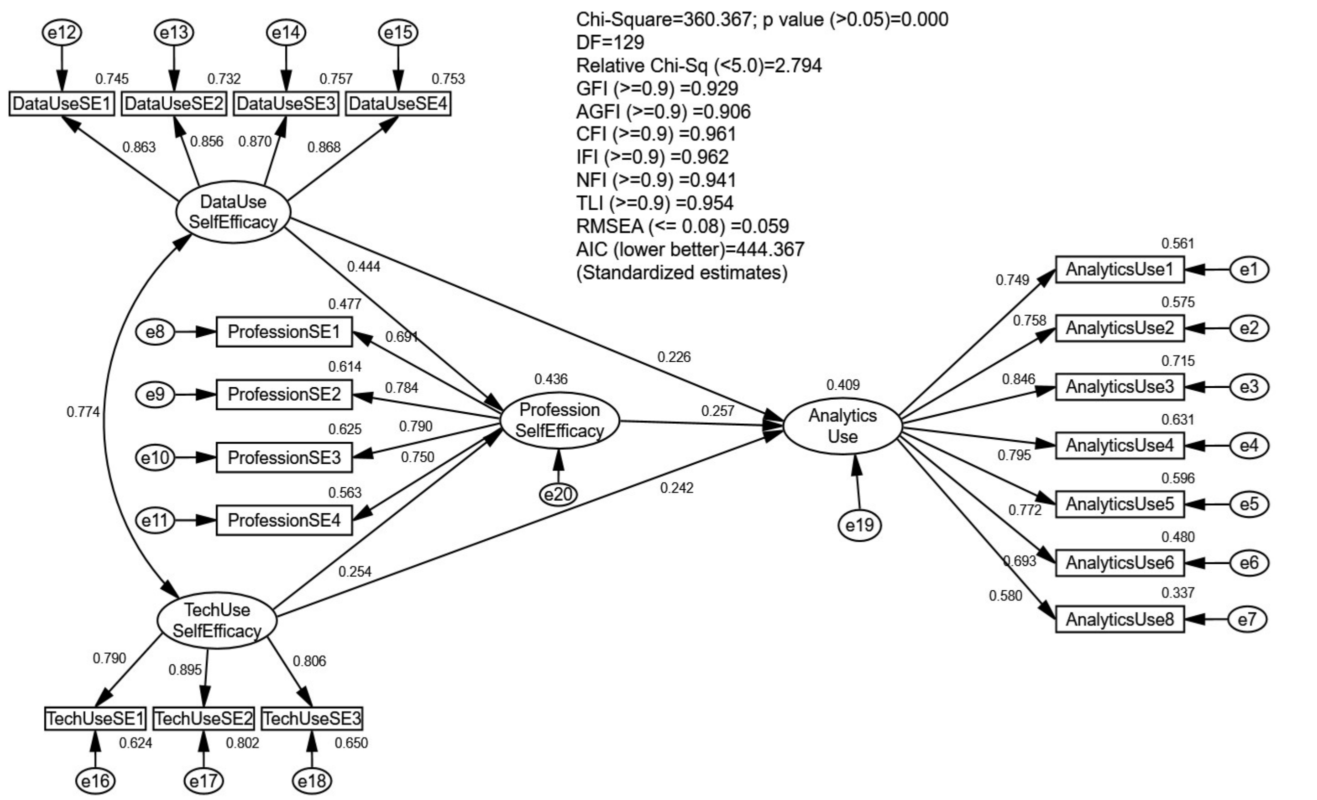


Fig. 2. Structural model.

Table 7. Causal path for professional use and analytics use

| Causal Path | b | Beta | CR | $p$ |
|---|---|---|---|---|
| Data Use SE → Professional SE | 0.321 | 0.444 | 5.865 | 0.000 |
| Technology Use SE → Professional SE | 0.205 | 0.254 | 3.394 | 0.000 |
| Data Use SE → Analytics Use | 0.339 | 0.226 | 4.292 | 0.000 |
| Technology Use SE → Analytics Use | 0.216 | 0.242 | 3.006 | 0.003 |
| Professional SE → Analytics Use | 0.259 | 0.257 | 3.303 | 0.000 |

Professional Self-Efficacy (R= 0.656; $R^2$ = 0.430); Analytics Use (R=0.640; $R^2$ = 0.409)

The structural model had two endogenous constructs: i) Analytics Use; and ii) Professional SE. The causal path shown in Table 7 showed that data use self-efficacy positively affects professional self-efficacy ($\beta = 0.444$; $p < 0.05$) and positively affects analytics use ($\beta = 0.226$; $p < 0.05$). Technology use self-efficacy positively affects professional self-efficacy ($\beta = 0.254$; $p < 0.05$) and positively affects analytics use ($\beta = 0.242$; $p < 0.05$). Professional self-efficacy positively affects analytics use ($\beta = 0.254$; $p < 0.05$). Data use, technology use, and professional self-efficacies explain 40.9% of the variance in analytics use. Meanwhile, 43.6% of the professional self-efficacy variance is defined by the respective data use and technology use self-efficacies. Therefore, there are moderate positive correlations between analytics use and professional, data use, and technology use self-efficacies. There are also small-to-moderate direct, indirect, and total effects between exogenous and endogenous variables of the study (Table 8).

Table 8. Direct, indirect, and total effects

| Path | Effects | | |
|---|---|---|---|
| | Direct | Indirect | Total |
| Data Use SE → Professional SE | 0.444 | - | 0.444 |
| Technology Use SE → Professional SE | 0.254 | - | 0.254 |
| Data Use SE → Analytics Use | 0.226 | 0.114 | 0.340 |
| Technology Use SE → Analytics Use | 0.242 | 0.065 | 0.307 |
| Professional SE → Analytics Use | 0.257 | - | 0.257 |

### *E. Bootstrap Test for Mediation Role*

The bootstrap method was used to determine the mediating role of professional self-efficacy in the relationship between technology use self-efficacy, data use self-efficacy and analytics use; the mediating construct standardized direct and indirect effects are summarized in Tables 9 and 10. The bootstrap results showed that the 95% confidence intervals for all the immediate effects of technology use on self-efficacy, data use self-efficacy, and analytics use did not intersect with zero. Moreover, the 95% confidence intervals for the indirect impact of data use self-efficacy on the analytics use through professional self-efficacy were 0.079–0.421, which also did not intersect with zero. The 95% confidence intervals for the indirect effect of technology use self-efficacy on the analytics through professional self-efficacy were 0.103–0.382, which also did not intersect with zero. Together, these results manifested that all direct and indirect effects were significant at the 0.05 level. Gerbing and Anderson [46] inferred that professional self-efficacy partially mediates between data use and analytics use and between technology use self-efficacy on analytics use.

Table 9. Data use SE → analytics use

| Hypothesized Path | | Beta | *p* | 95% Bootstrap BC CI | |
|---|---|---|---|---|---|
| | | | | LB | UB |
| Direct Model | Data Use SE → Analytics Use | 0.341 | 0.000 | 0.288 | 0.600 |
| Mediation Model | Data Use SE → Analytics Use | 0.226 | 0.003 | 0.079 | 0.421 |
| | Std. Indirect Effect (SIE) | 0.114 | 0.000 | 0.055 | 0.193 |

Table 10. Technology use SE → analytics use

| Hypothesized Path | | Beta | *p* | 95% Bootstrap BC CI | |
|---|---|---|---|---|---|
| | | | | LB | UB |
| Direct Model | Technology Use SE → Analytics Use | 0.306 | 0.000 | 0.081 | 0.367 |
| Mediation Model | Technology Use SE → Analytics Use | 0.242 | 0.000 | 0.103 | 0.382 |
| | Std. Indirect Effect (SIE) | 0.065 | 0.002 | 0.021 | 0.134 |

## V. Discussion and Implications

Leveraging technology and data in education is essential for shaping 21st-century learning and meeting the standards of the Fourth Industrial Revolution (IR4.0). Teachers believe that 4th IR technologies will be used in a wide range in the future to improve learning opportunities and keep student's data and activities for a long time. They referred that the teaching-learning processes will occur with no values and low level of students-teachers interactions. They also predicted that robots and machines will work instead of humans even in educational jobs in the future [47]. Teachers are not only expected to embrace and integrate technology and data into their methodologies but must also cultivate a reasonable sense of self-efficacy in their teaching profession. This is vital to ensure the effectiveness and sustainability of addressing the evolving educational requirements and responsibilities of the present era. In this regard, examining the professional self-efficacy of teachers utilizing technology and data in educational settings is a compelling endeavor. The incorporation of technology and data in the classroom contributes to elevated levels of anxiety and stress among teachers Fernández-Batanero *et al*. [48].

Studying teachers' self-efficacy in implementing LA is highly interesting, for they possess unique traits that differentiate them from other stakeholders in the education system [20]. LA use is a newly emerging approach that needs more empirical study to understand and better implement in teaching and learning practices [49]. It requires not just accessibility to technology or related data skills but also teachers' high self-efficacy toward their profession, technology use, and data use to affirm the effective and sustainable use of LA. In this study, analysis of teachers' use of LA can be summarized as they have experienced using LA in teaching practices. However, the course is still at a moderate level. This finding aligns with Fasiah *et al*. [50] which found that there was a moderate use of Google Classroom LA by teachers in schools.

The growing adoption of educational technologies, the rise of digital classroom concepts, and interest in big data innovations have heightened awareness of the potential for learning analytics in educational institutions to support learning development. Findings from the Systematic Literature Review (SLR) [12] support the findings, indicating that the implementation of LA in schools is still in an early stage, primarily occurring in developed countries. According to the SLR, most implementations focus on descriptive analytics, aimed at monitoring, analysis, and feedback. The SLR also highlighted a gap in research on learning analytics implementation at the primary and secondary education levels. Thus, examining the relationships and effects between TSE—professional, data use, technology use—and LA use provides nuanced details useful in proposing practical implications for implementing LA in teaching. The findings manifest that TSE and LA use have a positive relationship with each other concurrently. This aligns with the results reported by Clipa *et al*. [30], demonstrating elevated positive scores in areas such as the integration of information and communication technology into teaching practices, teachers' attitudes, self-efficacy, and technology skills.

Additionally, investigating the relationships and effects between professional self-efficacy, technology use self-efficacy, and data use self-efficacy provides nuanced details, which is significantly helpful in proposing practical solutions to the issue of insignificant use of LA. The findings manifest that technology use and data use have moderate positive relationships with both the professional self-efficacy and LA use of teachers. Aligned with Gomez *et al*. [6], positive relationships between the variables seem reliable and valid across different personal and contextual conditions. This aligns with a study by Abdullah *et al*. [51] indicated that teacher professional self-efficacy, technology use, and data use are at a moderate level. The findings demonstrate a positive correlation among these constructs. However, the connections are not influenced by factors such as age, gender, or school location.

The adoption of new technologies and the shift toward digitalization in education present considerable challenges for teachers, especially those accustomed to traditional teaching methods. Many teachers face difficulties adapting to new approaches, including the integration of technology into their teaching practices [52]. While some acknowledge the benefits and effectiveness of digital tools in education, not all are motivated to adopt and adapt to them. A significant number of teachers feel uncomfortable with technology use, often citing limited proficiency due to the time and effort needed to develop the required skills for effective classroom technology use [53]. Additionally, inadequate classroom facilities and a lack of technological resources hinder teaching activities, causing frustration among teachers [54]. Education stakeholders and policymakers should pay great attention to teachers' technology use and data use to improve their sense of self-efficacy toward the teaching profession, which contributes to increasing the use of LA in the classroom.

Moreover, a mediating association exists between professional self-efficacy in data use, technology use and LA use. These results support the propositions that previous research has concluded regarding the mediating role of professional or occupational self-efficacy between several constructs, such as job satisfaction, job insecurity, psychological well-being, and work engagement [22, 25, 26]. Positive relationships between the variables seem reliable and valid across different personal and contextual conditions. Education stakeholders and policymakers should pay great attention to teachers' professional self-efficacy to improve their performance and commitment, which contributes to the effective use of learning analytics.

Professional self-efficacy has been found to mediate the relationship between various professional factors, such as job satisfaction and career calling, in-role performance and career calling [22], work performance and work motivation [26], and job insecurity and job-related learning [25]. Consequently, several countries are working to address teacher shortages and early retirement by introducing supportive policies and enhanced services aimed at strengthening teachers' professional self-efficacy.

A study by McDonald and Siegall [55] found a positive correlation between technology use and multiple job satisfaction indicators, including increased commitment, work quality, and productivity, alongside a negative correlation with absenteeism and tardiness. Similarly, Medici *et al*. [56] observed that technology use was associated with decreased intentions for job changes, indicating its essential role in enhancing professional commitment and reducing turnover intentions. Conversely, Weibenfels *et al.* [57] suggested that technology use also contributes positively to shifts in classroom management practices. Research has also shown that perceived loyalty to one's career amid technological advancements can lead to feelings of job insecurity [58], which in turn affects job satisfaction, organizational commitment, and intentions to leave [59]. Consequently, integrating technology into classroom settings may present challenges for teachers, who are expected to adapt actively, potentially impacting their professional self-efficacy.

The collective findings of these studies underscore the multifaceted impact of technology in educational and professional settings. By enhancing job satisfaction, commitment, and retention, technology not only benefits teachers' professional experiences but may also contribute to more consistent and effective classroom environments. Additionally, technology's role in refining classroom management practices suggests it can be a valuable tool for developing efficient teaching strategies, ultimately improving learning outcomes.

To confirm the teaching profession's effectiveness, teachers' self-efficacy should be studied more in addressing their use of LA across diverse settings. Supported by past studies, the present study asserts that it is vital to understand how efficacious a teacher perceives doing their job, their technology use, and data use. As such, researchers, stakeholders, and policymakers are urged to collectively strive to provide teachers with the resources, working environments, and training they need to continue doing what they enjoy most—teaching. Consistent with social cognitive theory [20], these efforts could strengthen teachers' beliefs and convictions that they possess influence over conditions in the workplace, which can lead to improved and higher performance.

The findings emphasize the need for education stakeholders and policymakers to prioritize these aspects, recognizing their impact on teaching effectiveness and promoting the integration of data and technology in education. To achieve this, educational institutions should prioritize providing teachers with essential tools, training, and support to enhance their proficiency in technology use and data interpretation. Such can be accomplished through targeted professional development initiatives focusing on technology integration and the improvement of data literacy skills.

In real-world settings, these findings can guide the development of targeted professional development programs that empower teachers to confidently integrate learning analytics into their teaching. By focusing on enhancing professional self-efficacy, programs can help teachers overcome challenges related to data analysis and decision-making. Furthermore, by integrating collaborative projects, coaching, and peer support, these programs can make learning analytics more accessible and relevant to teachers, ultimately improving educational outcomes for students.

The substantial use of LA by school teachers in Malaysia is likely due to their belief in LA's frequent and effective application in teaching. By using LA, teachers gather, analyze, and interpret learning data for informed educational decisions and interventions. Employing various analytics techniques and tools enhances teachers' technological competencies and data literacy skills. Furthermore, engaging with data analytics supports teachers in developing competencies of technology and data use that benefit professional self-efficacy.

This study's findings contribute as well to the theory of technology use in understanding how specific factors directly and indirectly influence the implementation of LA, expanding the body of knowledge in this field. Some factors impact LA implementation directly or indirectly, while others serve as mediators. Each variable examined in this study proves to be a significant factor in successful LA adoption. The results support the notion that self-efficacy in technology use, data use, and professional competency can positively affect the use of LA among Malaysian school teachers.

## VI. Conclusion and Recommendations for Future Studies

In summary, this study delves into the critical association between teachers' self-efficacy in utilizing learning analytics within the context of Malaysian education. The findings reveal a notable correlation between the level of professional self-efficacy, the utilization of technology and data, and the implementation of learning analytics among teachers. This implies that teachers proficient in employing technology and data are more likely to possess an elevated sense of professional self-efficacy, indirectly influencing the increased use of learning analytics in the classroom. Notably, the link between technology use, data use, and learning analytics utilization is partially mediated by professional self-efficacy, underscoring the pivotal role of professional self-efficacy in fostering teachers' confidence in the effective integration of learning analytics into their teaching methodologies.

This study puts forward recommendations that could guide future research endeavors. Although teachers acknowledge the potential benefits of educational technologies, they often encounter challenges and feel overwhelmed during the adoption process. Future studies should explore both positive aspects and barriers of teachers' perspectives on technology and data use for successful micro-level implementation. Moreover, it remains unclear the extent of teachers' knowledge and competency in utilizing technology and data for learning improvement. Investigating the purposes and roles of teachers in using technology and data is essential in addressing their self-efficacy concerns in the field.

There are several limitations of this study. This study was conducted in the post-COVID-19 pandemic era, which can potentially impact respondents' perceptions of specific constructs. Additionally, all variables in this study relied on self-report measures, introducing the possibility of method bias. Subsequent research could explore alternative design methods, such as involving diverse education stakeholders to assess analytics use frequencies and mitigate potential biases associated with self-reporting.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

The authors, SHA and MHMP, confirm responsibility for research conception, literature review, methodology, data collection, analysis, interpretation of results, and manuscript preparation. MHMP also confirms the responsibility of supervising the research. The authors, MAAM and EM, confirm responsibility for research conception and in critically discussing the interpretation of the results and providing substantial revisions to the manuscript. All authors have read and approved the final version of the manuscript.

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