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Unlocking Tomorrow's Classrooms: Attitudes and Motivation Toward Data-Based Decision-Making in Teacher Education

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Abstract

In today's increasingly data-driven educational landscape, teachers are expected to use data to inform instructional decisions. However, effective data use depends not only on statistical competence but also on motivation, attitudes, and academic self-concept. This study examines how these factors influence student teachers' readiness to engage with standardized assessment data. A survey of 164 Flemish primary education student teachers assessed their motivation, attitudes toward data use, and academic self-concept. Cluster analysis identified four distinct profiles, ranging from highly competent yet disengaged users to low-performing but externally motivated individuals, highlighting significant variability in data engagement. A pre- and post-test study design involving an e-course on basic statistical concepts demonstrated that targeted instruction can enhance perceived competence, particularly in areas such as box plot interpretation. Findings suggest that technical training alone is insufficient to promote sustained data use; fostering intrinsic motivation, positive attitudes, and a strong academic self-concept is essential for long-term engagement with data.

Keywords: teacher professionalization; data-based decision-making; teacher education; standardized assessment

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1. Introduction

Data have become a powerful tool in education, shaping instructional practices and informing decision-making processes. The growing availability of educational data—from standardized assessments to classroom observations—offers valuable opportunities to improve teaching strategies and support student learning (Schildkamp et al., 2013; van Geel et al., 2016). Teachers are expected to integrate these data sources into their practice, using insights to tailor instruction and enhance learning outcomes. However, effective data use extends beyond technical skills; it also hinges on psychological factors such as motivation, attitudes, and self-perceived competence (Datnow & Hubbard, 2016; Sutherland, 2004). Without a positive disposition toward data, even well-trained educators may struggle to engage meaningfully with it.

Research highlights that teachers who feel confident in their data literacy skills and recognize the value of data are more likely to integrate it into their teaching (Mandinach & Gummer, 2016; Verhaeghe et al., 2010). Conversely, a lack of motivation or negative attitudes can create barriers to data use, regardless of a teacher's technical skills (Schildkamp & Kuiper, 2010; Vanlommel et al., 2016). As a result, fostering both cognitive and affective engagement with data is crucial for preparing educators to work in data-rich environments. Despite the growing emphasis on data use in education, little is known about how student teachers—as future educators—perceive their own readiness in this regard. Their motivation, attitudes, and academic self-concept regarding data use will shape their future teaching practices. Academic self-concept, in particular, plays a central role in determining whether individuals engage with data confidently or experience uncertainty and avoidance (Eccles & Wigfield, 2002; Marsh et al., 2017). While researchers have examined in-service teachers' perceptions of data use, there is a lack of insight into how student teachers develop these dispositions during their training.

This study addresses this gap by investigating student teachers' motivation, attitudes, and academic self-concept concerning data use. Using a survey-based approach, we identify distinct student teacher profiles and examine the impact of an intervention, in the form of an e-course, aimed at improving statistical competence. By understanding these psychological and competency-related factors, this research contributes to the development of teacher education programs that not only equip student teachers with technical skills but also foster a mindset conducive to sustained and meaningful data use.

2. Theoretical Framework

2.1. Data-Based Decision-Making in Teacher Education

Data-based decision-making (DBDM) refers to systematically collecting and analysing data sources within a school, applying the outcomes in teaching, curricula, and school performance, and implementing and evaluating the actions taken (Mandinach & Schildkamp, 2021; Schildkamp & Kuiper, 2010). Data literacy is a crucial requirement for DBDM (Ebbeler et al., 2016; Hoogland et al., 2016; Kippers et al., 2018; Mandinach & Gummer, 2016). It involves transforming data into actionable instructional knowledge by collecting, analysing, and interpreting data to inform instructional decisions (Mandinach & Gummer, 2016).

Schools of education offer a coherent instructional framework in which data literacy can be systematically integrated into teacher preparation. It is thus necessary to incorporate data literacy and DBDM into teacher education in order to enhance the number of teachers equipped with the requisite skills to use data effectively in the classroom (Kippers et al., 2018; Mandinach, 2012). Research undertaken by Mandinach and Gummer (2016) offers important insights into data literacy in the process of teacher development. Their study emphasizes the need for a system approach to build data literacy among educators. Three fundamental premises are formulated: (1) It is essential that DBDM is integrated into the training of educators. Educators need to get a comprehensive training in data use, ideally starting during their pre-service education and continuing throughout their professional lives. This aligns with the findings of Obery et al. (2020), where pre-service teachers emphasized the importance of integrating data consistently across all elements of teacher preparation, since they did not perceive data use as formally taught in their coursework and practicums. They felt that they did not know how to integrate DBDM into their teaching practices. This approach aims to promote the seamless incorporation of data into daily teaching practices, rather than viewing it as an additional task. (2) The necessary educational experiences must take place in schools of education. It is imperative for these schools to include data-driven methodologies and concepts into the instruction of educators. (3) Finally, there are several key players who need to create a conducive atmosphere for transformation, such as schools, practitioners who carry out the requirements of data use, professional development providers, state education agencies, and professional organizations.

2.2. Motivation Toward Data Use

While data literacy is a fundamental skill in teacher education, its successful application is not solely dependent on technical proficiency. Teachers' willingness to engage with data is shaped by their motivation, which determines whether they perceive data use as an opportunity for professional growth or as an administrative burden (Datnow & Hubbard, 2016; Vanlommel et al., 2016). Research suggests that motivation plays a pivotal role in determining whether teachers actively engage with data and integrate it into their instructional decision-making processes (Deci & Ryan, 2000; Vansteenkiste et al., 2007). Understanding the role of motivation is therefore crucial in supporting effective data use in educational practice. Self-Determination Theory (SDT) (Deci & Ryan, 2000) provides a comprehensive framework for understanding human motivation, emphasizing not only the quantity but also the quality of motivation (Vansteenkiste et al., 2007). A central aspect of SDT is how individuals internalize and regulate motivation along a continuum of autonomy. Within this framework, the Organismic Integration Theory (OIT) offers a more nuanced perspective on how extrinsic motivation can gradually become more self-regulated and internalized (Deci & Ryan, 1985; Deci & Ryan, 2000).

OIT conceptualizes motivation along a continuum that ranges from external regulation (compliance driven by external rewards or punishments), to introjected regulation (driven by internal pressures such as guilt), to identified regulation (valuing the activity as personally important), and ultimately to integrated regulation (where the activity is fully assimilated with one's values and identity), which closely resembles intrinsic motivation. Understanding this continuum is crucial for supporting sustained and meaningful data use in educational practice, as it highlights how teachers' and school leaders' motivations can evolve from externally controlled to more autonomous engagement.

In the context of educational data use, the degree of motivational autonomy plays a key role. Behavioral regulation helps clarify whether data-driven practices are approached from a sense of personal volition or external obligation (Vansteenkiste et al., 2007). Autonomous motivation—such as identified and internal regulation—encourages school administrators and teachers to engage with data because they find it meaningful and aligned with their professional values. For example, when school leaders perceive data use as contributing to their instructional goals, they are more likely to adopt it willingly.

Conversely, controlled motivation, including introjected and external regulation, can also drive behavior, though with different implications. Introjected regulation involves internal pressure, such as guilt or fear of disappointing others, leading educators to tie their self-worth to their data use. External regulation occurs when behavior is shaped primarily by external demands, such as seeking rewards or avoiding criticism. In such cases, educators may comply with data use mandates without genuine internal endorsement. In the absence of both autonomous and controlled motivation, amotivation may arise, characterized by feelings of helplessness and disengagement, where educators believe they lack the capacity to influence instructional quality through data (Deci & Ryan, 2000).

While autonomous motivation generally leads to more sustained and effective engagement (Vansteenkiste et al., 2007), it is important to acknowledge that controlled motivation can sometimes serve a pragmatic role, especially in the early stages of change. Ultimately, fostering a transition from controlled to autonomous forms of motivation is key to promoting long-term data use in schools (Sutherland, 2004). Recognizing that motivation is dynamic and context-dependent allows for a more flexible and realistic approach to supporting educators in this process. Table 1 provides an overview of these types of motivation as described by Deci and Ryan (2000).

Table 1. Self-determination theory by Deci and Ryan (2000).

	Types of Motivation				
	Autonomous motivation		Controlled motivation		Amotivation
Level of motivation	High	High	High	High	Low
Type of motivation	Intrinsic	Extrinsic	Extrinsic	Extrinsic	Amotivation
Type of regulation	Intrinsic	Identified	Introjected	External regulated	Not regulated
Underlying emotions	Willingness, freedom	Willingness, freedom	Stress, pressure	Stress, pressure	Apathy, helplessness

2.3. Attitudes Toward Data Use

While motivation determines whether teachers engage with data and to what extent they persist in using it (Deci & Ryan, 2000; Vansteenkiste et al., 2007), their attitudes shape how they perceive and emotionally respond to data use (Datnow & Hubbard, 2016; Vanhoof et al., 2014). Even if teachers feel externally or internally motivated to work with data, negative attitudes—such as scepticism toward its validity or a lack of confidence in interpreting data—can still hinder meaningful engagement (Kowalski & Lasley, 2008; Schildkamp et al., 2013). Understanding attitudes is, therefore, essential, as they influence whether teachers experience data use as an enriching tool for instructional improvement or as an additional burden (Datnow & Hubbard, 2016; Verhaeghe et al., 2010).

When examining the complexities of attitudes toward data use, it is clear that there is an interplay between cognitive and affective components. The cognitive component comprises a broad spectrum of thoughts and perceptions that underpin the opinions of educators regarding the efficacy of data. These comprise not only the perceived usefulness of data, but also the extent to which it is regarded to contribute significantly to the formation of educational policies and practices inside schools (Sanbonmatsu & Fazio, 1990). Conversely, the affective component of attitudes toward data comprises the emotional responses and subjective experiences encountered by both school administrators and teachers. These emotions have a key influence in defining the decisions and actions taken regarding data use. They determine the degree of comfort or discomfort experienced by educators when dealing with data in various circumstances, as well as their enthusiasm or fear about incorporating data into their professional actions (Sanbonmatsu & Fazio, 1990).

A striking observation from previous research is the tendency for individuals to prioritize their affective attitudes over their cognitive ones when it comes to behavioral decision-making (Sanbonmatsu & Fazio, 1990). In the context of data use, this suggests that educators may not exclusively rely on their knowledge and attitudes regarding data use but are also highly impacted by their emotional responses to data-related circumstances (Vanhoof et al., 2014). This delicate interplay between cognitive and emotional components underlines the complexity of attitudes toward data use and their impact on educational methods. By noticing and understanding both dimensions, teachers can get deeper insights into the factors driving data use within educational contexts.

Figure 1 provides an overview of the influence of attitudes and motivation on teachers' data use.

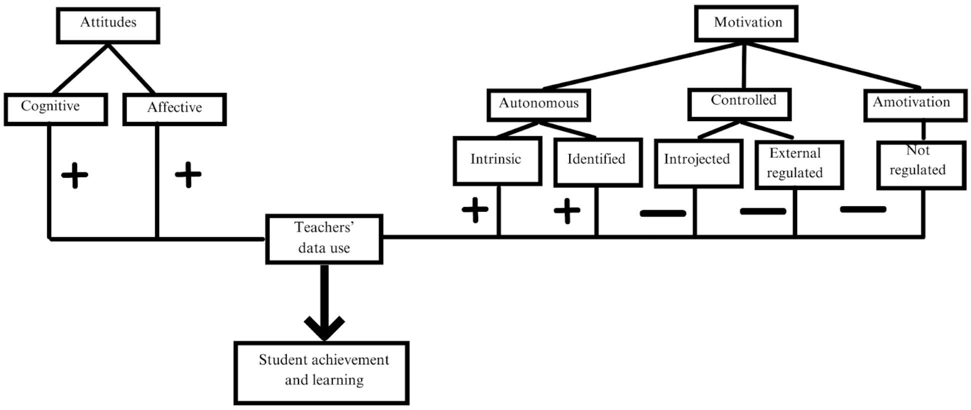

Figure 1. Influence of attitudes and motivation on teacher's data use. + positive impact on teachers' data use. - negative impact on teachers' data use. Teachers' data use has a positive impact on student achievement and learning.

2.4. Academic Self-Concept

Beyond motivation and attitudes, teachers' engagement with data is also influenced by how they perceive their own competence. Academic self-concept—the set of traits and qualities that a person attributes to themselves within the academic field—plays a crucial role in determining whether they approach data with confidence or hesitation. A positive self-concept can reinforce motivation, while a negative self-concept may lead to avoidance of data-related tasks. This concept forms the cognitive representation of an individual's academic identity and performance (Eccles & Wigfield, 2002; Marsh et al., 2017). Academic self-concept is widely recognized as a domain-specific construct (Marsh et al., 2018; Bong & Skaalvik, 2003), meaning that individuals may hold differing perceptions of competence across different subject areas or skill domains. In the context of this study, academic self-concept specifically refers to student teachers' perceived competence in working with educational data and statistical concepts. Furthermore, research indicates that individuals with a strong academic self-concept are more likely to engage in learning activities and persist in challenging tasks (Chang et al., 2022; Granero-Gallegos et al., 2021). In the context of data use, a positive self-concept can reinforce motivation and encourage teachers to actively incorporate data-driven decision-making, whereas a negative self-concept may lead to the avoidance of data-related tasks (Demanet & Van Houtte, 2019; Verhaeghe et al., 2010)

3. The Present Study

In a data-driven educational landscape, not only must teachers possess statistical competence; they must also be motivated and confident in their ability to use data effectively (Datnow & Hubbard, 2016; Mandinach & Gummer, 2016). While previous research has explored teachers' attitudes, motivation, and academic self-concept separately, little is known about how these factors interact in shaping student teachers' engagement with data use. It is likely that student teachers do not form a homogeneous group in this regard, but instead exhibit distinct profiles characterized by varying levels of motivation, attitudes, and perceived statistical competence. Identifying these profiles is crucial for developing targeted training interventions that cater to different learner needs, rather than applying a one-size-fits-all approach to data literacy education.

This study investigates how student teachers engage with standardized assessment data, a data source that became available to schools in Flanders in spring 2024. Standardized assessments provide objective, comparable measures of student learning, offering valuable insights that can guide instructional decision-making and school improvement efforts. Given that student teachers are at the beginning of their professional journey, understanding their motivation, attitudes, and self-concept regarding standardized assessment data is essential for preparing them to integrate these data into their future teaching practice.

To gain a more comprehensive understanding of these factors, we go beyond treating them as isolated constructs and examine their interaction. By applying a cluster analysis, we identify distinct student teacher profiles based on motivation, attitudes, and academic self-concept regarding standardized assessment data. Additionally, we investigate whether an e-course on basic statistical concepts can influence student teachers' self-concept and preparedness for data-informed teaching. Since standardized assessment data require teachers to interpret statistical patterns, trends, and distributions, strengthening student teachers' statistical competence is a critical step in ensuring their effective engagement with these assessments. Through a pre- and post-test design, we assess whether this study design impacts their self-perceived competence in working with data.

By identifying meaningful student teacher profiles and assessing the impact of the e-course, this study aims to provide insights into how teacher education programs can better support future educators in developing the necessary skills, confidence, and intrinsic motivation for the use of data obtained from standardized assessment. This leads to the following research questions:

1. What are the **motivations and attitudes** of student teachers toward data use?
   - How do student teachers perceive the importance of data use in their forthcoming teaching roles?
2. What is the **academic self-concept** of student teachers regarding data use?
   - Does this improve after completing an e-course on basic statistical concepts?
3. What **student teacher profiles** can be identified based on motivation, attitudes, and academic self-concept regarding data use?
   - To what extent do these profiles differ based on background characteristics, such as exam scores during the last exam period, prior education, and gender?

4. Methodology

This section outlines the participants, research design, data collection process, and analytical methods used in the study. It describes the participants, the structure of the surveys and e-course, and the measures used to assess attitudes, motivation, and academic self-concept regarding data use. Additionally, the statistical analyses conducted to identify student teacher profiles and examine background differences are explained. Finally, the approach to analyzing open-ended responses is discussed.

4.1. Participants

Primary teacher education programs in Flanders, Belgium, were selected for this study because data-informed teaching is a current focus in Flemish educational policy. Moreover, primary school teachers already have experience working with, for example, various forms of standardized assessments, which makes data literacy a particularly relevant and immediately applicable competence for this group. Targeting primary teacher education programs also ensured a well-defined and comparable participant population for the study.

All the primary teacher education programs in Flanders, Belgium, were contacted to participate. A total of 164 student teachers from seven different primary teacher education programs in Flanders participated in the study. In total, there are 16 officially recognized primary teacher education programs in Flanders. The exact response rate could not be calculated, as enrollment data per program was not available. Table 2 provides an overview of the participants.

Table 2. Overview of the participants.

Variable	Category	Frequency	%
Gender	Male	20	12.2
	Female	143	87.2
	Other	1	0.6
Prior educational track	General education	75	45.7
	Technical education	80	48.8
	Vocational education	6	3.7
	Arts education	3	1.8
Student Year [1]	First year	0	0
	Second year	81	49.4
	Third year	55	33.5
	Combination first–second year	9	5.5
	Combination second–third year	19	11.6

Note: Combination first–second year" and "second–third year" refer to students enrolled in coursework spanning both academic years concurrently. [1] In Flanders, a teacher education program lasts for three years.

All participants provided informed consent prior to participation. Ethical approval for this study was granted by the Social and Societal Ethics Committee (SMEC) of Hasselt University, under approval number REC/SMEC/2022-23/23.

4.2. Data Collection

The participants first completed an initial survey, followed by participation in an e-course. Upon completion of the e-course, student teachers completed a second survey. Table 3 provides an overview of the data collection process.

Table 3. Overview of data collection.

Parts of the Data Collection	Content
Survey	• Data use • General information (gender, home language, nationality, scholarship) • Educational information (current education, secondary education, mean score previous school year) • Pre-test basic statistical elements • Pre-test academic self-concept
E-course	• Information regarding standardized assessment in Flanders • Data use in education • Course on basic statistical elements
Survey	• Post-test basic statistical elements • Attitudes regarding data use • Motivation regarding data use • Post-test academic self-concept

Note: The pre-test, e-course, and post-test were administered consecutively within a single, supervised 3 h session conducted on the same day.

The pre- and post-test on basic statistical elements contained seven questions pertaining to the mean, median, box plots, graphs, and tables, with an emphasis on accurately interpreting these elements. The five statistical concepts addressed in the e-course were selected because they represent the most commonly used elements in feedback reports of, for example, standardized assessments in Flemish education. The selection was intended to ensure alignment with authentic data use contexts and to support the development of practically relevant data literacy skills for student teachers. Multiple-choice questions with four possibilities were incorporated, as well as questions with the options 'correct', 'incorrect', and 'I don't know'.

The pre- and post-test of academic self-concept contained five questions. Two question blocks were included in the pre-test to assess participants' self-estimation of basic statistical concepts. Respondents indicated their familiarity with the mean, the median, box plots, graphs, and tables using a Likert-type scale ranging from 1 (indicating no knowledge) to 5 (indicating extensive knowledge). Additionally, respondents were asked to rate their ability to interpret these components on a Likert scale from 1 (indicating complete disagreement) to 5 (indicating complete agreement), with the option 'I don't know' available. For the internal consistency of the scales, we used Cronbach's alpha (α), a commonly used measure for internal consistency. Values above 0.6 are generally considered acceptable (Haynes et al., 1995). A Principal component analysis was conducted on this pre-test, revealing three components. Component 1, labelled "Statistical Summary" ($\alpha = 0.86$), comprised items related to medians and means, showing a shared underlying characteristic of statistical summary. Component 2, labeled "Box plot", included one item, namely that of the box plot. Component 3, labelled "Visual Presentation" ($\alpha = 0.92$), included items related to tables and bar charts, indicating that these items share a common underlying characteristic related to visual data presentation.

The student teachers completed an e-course that covered several topics: (1) information regarding the centralized tests in Flanders, detailing their structure, purpose, and implementation; (2) the importance of data use in educational settings; and (3) several basic statistical concepts, including the mean, median, and box plots. Various interactive elements were incorporated, including instructional video clips and exercises. The completion of the e-course took approximately one hour.

The online survey on attitudes and motivation regarding data use, conducted via Qualtrics, incorporated validated scales from previous research to measure teachers' motivation to engage with standardized assessment data (Molenberghs et al., 2023) and their attitudes toward the use of pupil learning outcomes (Van Gasse et al., 2017a, 2017b). The original motivation items, adapted and translated for the Dutch-speaking context, were subjected to a reliability analysis. Following this, and in line with previous research (e.g., Vansteenkiste et al., 2007), we merged intrinsic motivation and identified regulation into a composite scale for autonomous motivation ($\alpha = 0.81$) and combined introjected and external regulation into a scale for controlled motivation ($\alpha = 0.86$). This decision was supported by higher internal consistency (Cronbach's alpha) for the merged scales compared to their individual components. A third scale, no regulation, contained three items ($\alpha = 0.78$). To confirm the two-dimensional motivational structure, a principal component analysis (PCA) was conducted, which further supported the distinction between autonomous and controlled motivation. Respondents rated their agreement on a 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). Table 4 provides an overview of the scales and their corresponding reliability coefficients, which range from 0.73 to 0.92.

Student teachers' attitudes toward data use were assessed only after completion of the e-course. This timing was chosen to align with the study's focus on post-intervention perceptions but does not allow for direct assessment of attitudinal change resulting from the intervention.

Table 4. Overview of the survey scales with example items.

Scale	Number of Items	Cronbach's Alpha
Motivation		
Autonomous motivation	6	0.81
'I find the feedback from the standardized assessments very interesting to work with.'		
Controlled motivation	6	0.86
'I plan to work with the feedback from the standardized assessments because I am expected to do so.'		
No regulation	3	0.78
'The reasons for working with the feedback from the standardized assessments are not clear to me.'		
Attitudes		
Cognitive	3	0.73
'I am convinced that working with data is valuable.'		
Affective	3	0.83
'I feel comfortable in a data-rich environment.'		
Pre-test academic self-concept		
Pre-test—statistical summary	2	0.86
Pre-test—visual presentation	2	0.92

4.3. Analysis

The analysis was conducted in SPSS (Version 29.0.2.0.20). The analysis component of this study involved multiple stages. First, a descriptive analysis was performed to provide a summary of the data. Given the ordinal nature of the Likert and Likert-type scales used in this study, we report both medians and interquartile ranges (IQR) to provide an appropriate and robust summary of the data. Means and standard deviations are also presented for comparison, as is common practice in educational research, but all inferential analyses were conducted using non-parametric tests aligned with the data characteristics.

To identify distinct student teacher profiles, a cluster analysis was conducted. A hierarchical cluster analysis (HCA) was first applied using Ward's method and squared Euclidean distance to determine the optimal number of clusters. The agglomeration schedule and dendrogram were examined to identify the point at which the largest increase in fusion distance occurred, indicating the most appropriate cluster solution. An agglomeration schedule displays the stages of hierarchical clustering and indicates how cases or clusters are merged at each step, helping to determine the appropriate number of clusters. A dendrogram is a tree-like diagram that visually represents the clustering process and the relationships between cases or clusters. Based on these results, a K-means clustering algorithm was subsequently applied to classify participants into the identified clusters. This method allowed for a more refined classification by iteratively adjusting cluster membership to minimize within-group variance. The final cluster centers were analyzed to interpret the characteristics of each group, providing insight into how student teachers differed in motivation, attitudes, and academic self-concept regarding data use.

After defining the clusters, inferential statistics were used to examine whether background variables significantly differed across clusters. A chi-square test was performed to determine whether prior education was distributed differently across the clusters. In addition, a Kruskal–Wallis test was conducted to assess whether academic performance, measured by the average score from the last examination session during their teacher training, and the number of weekly mathematics hours in secondary education varied significantly between clusters. Since these variables were ordinal in nature, this non-parametric test was deemed appropriate for comparing distributions across multiple independent groups.

The combination of cluster analysis and inferential statistics provided insights into the underlying structure of student teacher motivation, attitudes, and academic self-concept regarding data use. While the clustering approach helped uncover distinct profiles, additional statistical tests (chi-square test and Kruskal–Wallis test) allowed for an investigation of whether background characteristics played a role in shaping these profiles. Table 5 provides a summary of the statistical approach used.

Table 5. Summary of the statistical approaches.

Research Question	Analysis Type	Method Used	Purpose
RQ 1 + 2	Descriptive statistics	Means, standard deviations	Summarizing data characteristics
RQ 3	Cluster analysis	Hierarchical (Ward's) + K-means	Identifying distinct student teacher profiles
RQ 3	Chi-square test	Cross-tabulation	Examining differences in prior education across clusters
RQ 3	Kruskal–Wallis test	Rank-based comparison	Assessing differences in academic performance and mathematics instruction hours across clusters

For the analysis of the open-ended question "For what can data use be useful?", similar responses were grouped together. This involved identifying common themes or purposes mentioned by the participants regarding the purpose for which data can be used.

5. Results

In this section, the results of the research questions are presented. Explanatory findings follow descriptive findings in each section.

5.1. Research Questions 1 and 2—Motivation and Attitudes Toward Data Use

As presented in Table 6, student teachers reported the highest scores on the autonomous motivation scale (median = 4.00, IQR = 3.50–4.00; M = 3.73, SD = 0.45), suggesting that they primarily engage with data use out of intrinsic interest and personal relevance. This indicates that many student teachers recognize the educational value of data use as part of instructional decision-making.

Table 6. Motivation toward data use.

Scales	N	Minimum	Maximum	Mean	SD	Median	IQR
Autonomous motivation	160	2	5	3.73	0.45	4.00	0.5
Controlled motivation	160	1	4	2.83	0.71	3.00	1.00
No regulation	160	1	4	2.11	0.60	2.00	0.33
Total	160						

Controlled motivation yielded a moderate score (median = 3.00, IQR = 2.50–3.50; M = 2.83, SD = 0.71), indicating that some students are driven by external expectations, such as institutional demands or performance evaluations.

The lowest scores were found on the no regulation scale (Median = 2.00, IQR = 1.75–2.08; M = 2.11, SD = 0.60), reflecting that only a minority of student teachers are amotivated regarding data use. This suggests that most participants exhibit at least some form of motivation—either intrinsic or extrinsic—toward using educational data.

As shown in Table 7, student teachers reported high levels of cognitive attitudes toward data use (Median = 4, IQR = 0.67; M = 4.38, SD = 0.48), while their affective attitudes were notably lower (Median = 2.00, IQR = 0.67; M = 2.34, SD = 0.60). The high cognitive attitude scores suggest that student teachers recognize the importance and usefulness of data use in education. Cognitive attitudes encompass rational and knowledge-based evaluations, indicating that student teachers generally understand and acknowledge the benefits of data-driven decision-making for student learning and instructional improvement.

Table 7. Attitudes toward data use.

Scales	N	Minimum	Maximum	Mean	SD	Median	IQR
Cognitive	164	2.00	5.00	4.38	0.48	4.00	0.67
Affective	162	1.00	4.00	2.34	0.60	2.00	0.67
Total	162						

However, the low affective attitude score suggests that student teachers have a weaker emotional connection to data use. This implies that while they accept the significance of data intellectually, they may not feel comfortable or enthusiastic about engaging with it in practice. A low score in this domain may indicate a lack of emotional investment or even discomfort with data-related tasks. This may also be due to the fact that they are not yet actively teaching and do not have their own classroom or data with which to work; later, this might change.

When asked to select data from a given list that could be used in their teaching practice, almost all student teachers selected all the given data, except for the results of standardized tests (73.8%). Student teachers also reported this type of data as the least relevant (median = 4.00, IQR = 0; M = 3.89) and conversations with students as the most relevant (median = 5, IQR = 1; M = 7.79), as shown in Table 8. The percentages in Table 8 represent the proportion of participants who rated each data source as useful, defined as a score of 4 ("useful") or 5 ("very useful") on a 5-point Likert scale.

Table 8. Reported data that can be used and its relevance.

	Percent	Minimum	Maximum	Mean	SD	Median	IQR
Observations of students	97.6	3	5	4.71	0.53	5.00	1
Conversations with students	94.5	3	5	4.79	0.46	5.00	0
Results of class tests	91.5	1	5	4.22	0.78	4.00	1
Conversations with parents	89	2	5	4.35	0.67	4.00	1
Conversations with colleagues	84.8	2	5	4.01	0.75	4.00	1
Results of standardized tests	73.8	2	5	3.89	0.67	4.00	0
Other information	8.5						

Regarding the use of data, student teachers indicated that it could be used to differentiate, understand, and get to know the student, adjust their own teaching practices, gain insight into the students' entering characteristics, and obtain an overview of the growth and progress of the student. Table 9 provides an overview of the student count and indicates the number of respondents who selected each reason. Multiple responses were possible.

Table 9. Use of data.

Topic	Student Count
To differentiate	48
To understand and get to know the student, explore what they can or cannot do	25
To adjust your own teaching and reflect upon your teaching	20
To gain insight into the initial situation	12
To obtain an overview of the growth and progress of the student	6

5.2. Research Question 2—Student Teachers' Academic Self-Concept

As shown in Table 10, student teachers reported high levels of self-estimated knowledge and interpretation of the most basic statistical concepts. The mean scores indicate that participants felt particularly confident in their knowledge of means (median = 5, IQR = 0; M = 4.79, SD = 0.42), medians (Median = 5, IQR = 1; M = 4.66, SD = 0.70), tables (median = 5, IQR = 1; M = 4.57, SD = 0.53), and bar charts (median = 5, IQR = 1; M = 4.54, SD = 0.59). Similarly, the self-reported ability to interpret these concepts was relatively high, with means ranging between 4.48 and 4.59, with a standard deviation below 1 indicating little variation among respondents and high medians.

Table 10. Self-estimated knowledge and interpretation of statistical concepts (pre- and post-test, with Wilcoxon results).

Concept	Pre-Test Median (IQR)	Pre-Test M (SD)	Post-Test Median (IQR)	Post-Test M (SD)	Wilcoxon Z	Significance (p)
Knowledge						
Mean	5 (5–5)	4.79 (0.42)	/	/	/	/
Median	5 (4–5)	4.66 (0.70)	/	/	/	/
Box plot	3 (2–5)	2.52 (1.83)	/	/	/	/
Table	5 (5–5)	4.57 (0.53)	/	/	/	/
Bar chart	5 (5–5)	4.54 (0.59)	/	/	/	/
Interpretation						
Mean	5 (4–5)	4.59 (0.52)	5 (4–5)	4.49 (0.55)	−2.21	$p < 0.05$
Median	5 (4–5)	4.48 (0.70)	4 (4–5)	4.46 (0.58)	−0.67	n.s.
Box plot	3 (2–4)	2.81 (1.37)	4 (4–5)	4.10 (0.79)	−7.89	$p > 0.001$
Table	5 (4–5)	4.49 (0.55)	4 (4–5)	4.47 (0.54)	−0.58	n.s.
Bar chart	5 (4–5)	4.48 (0.61)	4 (4–5)	4.47 (0.54)	−3.96	$p < 0.001$

Note: Negative Z values indicate that post-test scores were systematically higher than pre-test scores. n.s.—not significant.

However, a notable exception was observed for box plots, where participants reported lower levels of both knowledge (median = 3, IQR = 3; M = 2.52, SD = 1.83) and interpretation (median = 3, IQR = 2; M = 2.81, SD = 1.37). This suggests that, compared to other statistical elements, student teachers are less familiar with box plots, and may require additional instruction and practice to interpret them. The standard deviation was high, indicating great variation among respondents.

Following the completion of the e-course, student teachers' self-estimation of their interpretation skills improved across all assessed components. While interpretation scores for means (median = 5, IQR = 0; M = 4.49), medians (median = 4, IQR = 1; M = 4.46), tables (median = 4, IQR = 1; M = 4.47), and bar charts (median = 4, IQR = 1; M = 4.47) remained relatively stable, the most substantial improvement was observed for box plots (median = 4, IQR = 1; M = 4.10, SD = 0.79).

To assess the impact of the e-course on statistical concepts, student teachers completed a pre-test and post-test in which they estimated their knowledge and interpretation skills for key statistical elements. To determine whether the observed differences between the pre-test and post-test scores were statistically significant, a Wilcoxon Signed-Rank test was conducted. This non-parametric test was chosen as it is appropriate for paired samples where normality cannot be assumed. Table 10 presents the mean scores for the pre- and post-test, the calculated difference (ΔM), and the Wilcoxon test results (Z-values and p-values) to quantify the observed growth.

The Wilcoxon Signed-Rank test confirmed that the increase in self-estimated box plot interpretation ability was highly significant ($Z = -7.89$, $p < 0.001$), indicating that the e-course had an impact on improving students' understanding of box plots—an area where they initially reported lower confidence. A smaller, but still statistically significant, decrease was observed for self-estimated mean interpretation ($Z = -2.21$, $p < 0.05$). This may suggest a calibration effect, where students, after gaining more knowledge, became more aware of gaps in their understanding and adjusted their self-perception accordingly. No significant differences were found for median and table interpretation, and the minor decrease in bar chart interpretation ($Z = -3.96$, $p < 0.001$), while statistically significant, was low.

5.3. Research Question 3—Student Teachers' Profiles

The cluster analysis identified four distinct clusters, each representing a unique student teacher profile regarding motivation, attitudes, and academic self-concept in data use. The distribution of participants across these clusters was Cluster 1 (n = 44), Cluster 2 (n = 18), Cluster 3 (n = 56), and Cluster 4 (n = 29), indicating variations in group size. Table 11 presents the final cluster centers, showing the mean scores for each variable within the identified groups. These profiles are visually summarized in Figure 2.

Table 11. Final cluster centers.

Variable	Cluster 1 (n = 44)	Cluster 2 (n = 18)	Cluster 3 (n = 56)	Cluster 4 (n = 29)
Autonomous motivation (0–5)	3.73	3.71	3.71	3.69
Controlled motivation (0–5)	2.78	2.94	2.97	2.55
Test basic statistical concepts (Total) (0–70)	60	22.78	47.50	70
Self-concept: mean/median interpretation (0–5)	4.56	4.03	4.58	4.71
Self-concept: tables/graphs interpretation (0–5)	4.59	4.14	4.45	4.62
Self-concept: box plot interpretation (0–5)	3.00	2.00	3.00	4.00
Cognitive attitudes (0–5)	4.39	4.28	4.46	4.29
Affective attitudes (0–5)	2.27	2.65	2.40	2.09

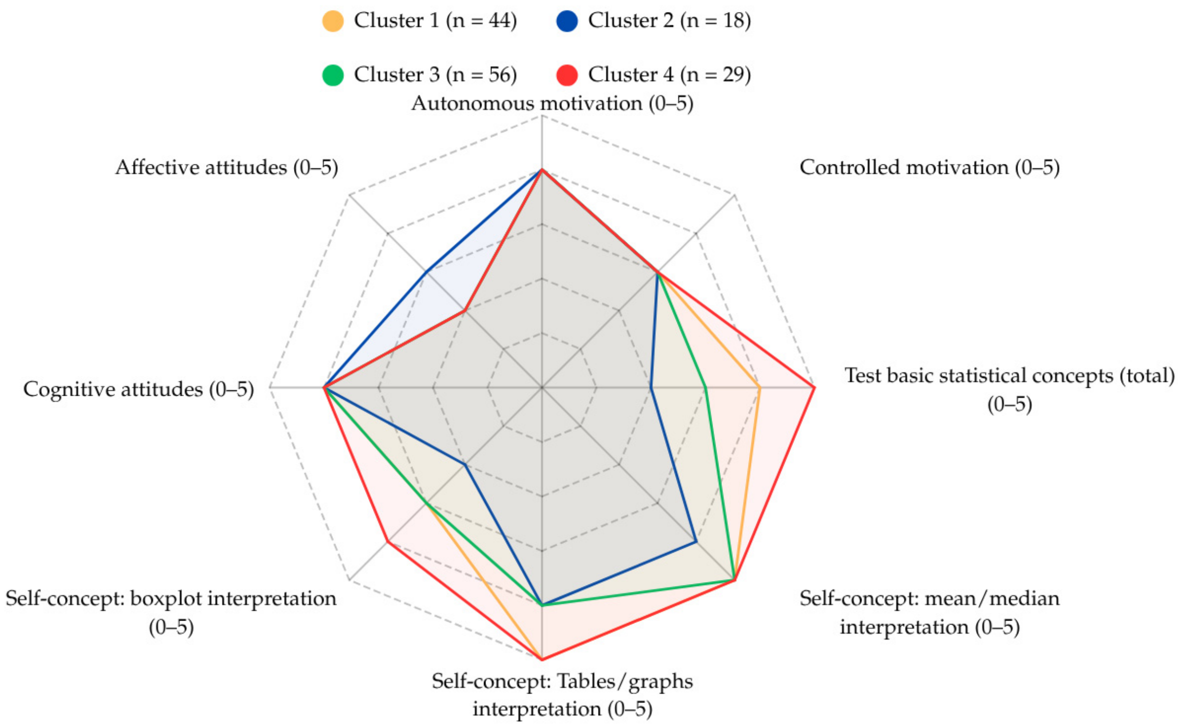

Figure 2. Overview of the clusters.

5.3.1. Cluster 1: "Competent but Emotionally Detached Users"

Participants in this cluster demonstrated high statistical competence, as reflected in their relatively strong test scores (M = 60.00 out of 70) and confidence in interpreting statistical concepts, including measures of central tendency (M = 4.56), tables and graphs (M = 4.59), and box plots (M = 3.00). Their cognitive attitudes toward data were strong (M = 4.39), indicating a rational appreciation of data use. However, their affective attitudes were among the lowest (M = 2.27), suggesting limited emotional engagement with data. Motivation levels were moderate, with autonomous motivation at M = 3.73 and controlled motivation at M = 2.78, indicating that these participants intend to use data without strong intrinsic interest or external pressure.

5.3.2. Cluster 2: "Low-Performing, Externally Driven Users"

This cluster had the lowest scores (M = 22.78) on the pre-test on basic statistical concepts, indicating limited statistical competence. Participants also had lower self-concept scores in interpreting statistical data, particularly for tables and graphs (M = 4.14) and measures of central tendency (M = 4.03). Despite their low competence, they exhibited the highest affective attitudes (M = 2.65), suggesting that they had a relatively positive emotional response to data use. Their motivation was more externally driven, with controlled motivation (M = 2.94) slightly higher than in other clusters. However, their autonomous motivation (M = 3.71) remained comparable to other groups, suggesting that although they faced challenges in data interpretation, they did not entirely reject its value.

5.3.3. Cluster 3: "Moderate Performers with External Motivation"

Participants in this cluster had mid-range statistical competence, scoring M = 47.50 on the test. Their self-concept in data interpretation was also moderate, with scores for interpreting measures of central tendency (M = 4.58) and tables and graphs (M = 4.45) positioned between the highest and lowest performing clusters. Unlike Cluster 1, they exhibited the highest level of controlled motivation (M = 2.97), suggesting that they were more likely to engage with data due to external pressures, rather than intrinsic interest. Their affective attitudes (M = 2.40) were relatively low, similar to Cluster 1, but their cognitive attitudes (M = 4.46) remained strong, indicating that they understood the value of data use even if they did not find it particularly engaging.

5.3.4. Cluster 4: "Highly Competent but Disengaged Analysts"

This cluster contained participants with the highest test scores (M = 70.00), reflecting a strong ability to analyze and interpret statistical data. Their self-concept in interpreting key statistical measures was also the highest, with scores of M = 4.71 for measures of central tendency and M = 4.62 for tables and graphs. Despite their high competence, this group had the lowest levels of controlled motivation (M = 2.55), suggesting they did not feel external pressure to engage with data. Furthermore, their affective attitudes were the lowest among all clusters (M = 2.09), indicating a lack of emotional investment in data use. Their cognitive attitudes were moderate (M = 4.29), showing that they acknowledged the importance of data use, but did not exhibit enthusiasm toward it.

5.3.5. Summary of Cluster Differences

The findings suggest that student teachers differ not only in statistical competence but also in their motivation and attitudes toward data use. While some clusters demonstrated strong analytical skills but low emotional engagement (Clusters 1 and 4), others struggled with data interpretation but maintained a more positive outlook toward its use (Cluster 2). Meanwhile, Cluster 3 represented a group of students who engaged with data primarily due to external pressures, rather than intrinsic interest. The variation in motivation types and affective responses suggests that study designs aimed at improving data literacy should consider not only technical training, but also strategies to enhance students' intrinsic engagement with data.

5.3.6. Statistical Significance Tests for Background Variables

To examine whether background characteristics varied significantly across clusters, statistical tests were performed. A Chi-square test was conducted to assess whether the distribution of prior education (secondary education) differed significantly between clusters. The results revealed a statistically significant association, $\chi^2(9) = 22.691$, $p = 0.007$, indicating that student teachers with different prior education backgrounds were not evenly distributed across the four clusters. An analysis of column percentages within the cross-tabulation (Table 12) shows distinct differences in how students from various educational tracks were distributed across the clusters.

Table 12. Cluster distribution by prior education.

Cluster	General Secondary Education (n = 69)	Technical Secondary Education (n = 70)	Arts Secondary Education (n = 2)	Vocational Secondary Education (n = 6)	Total (n = 147)
Cluster 1	25 (36.2%)	17 (24.3%)	1 (50.0%)	1 (16.7%)	44 (29.9%)
Cluster 2	5 (7.2%)	9 (12.9%)	0 (0.0%)	4 (66.7%)	18 (12.2%)
Cluster 3	27 (39.1%)	28 (40.0%)	0 (0.0%)	1 (16.7%)	56 (38.1%)
Cluster 4	12 (17.4%)	16 (22.9%)	1 (50.0%)	0 (0.0%)	29 (19.7%)
Total	69 (100%)	70 (100%)	2 (100%)	6 (100%)	147 (100%)

The results suggest that prior education is associated with differences in statistical competence, motivation, and attitudes toward data use. Students from general secondary education are predominantly found in Cluster 1 and Cluster 3, indicating that they tend to demonstrate moderate-to-high statistical competence. This suggests that they generally possess the foundational skills needed for data interpretation and may have developed a stronger self-concept regarding their statistical abilities. Similarly, students from technical secondary education are mostly represented in Cluster 3 and, to a lesser extent, Cluster 1, indicating that while they engage with data, there is more variation in their competence and motivation. The relatively low presence of students from technical education in Cluster 2 suggests that they are less likely to belong to the low-performing, externally motivated group.

Students from arts secondary education are evenly distributed between Cluster 1 and Cluster 4 but completely absent from Cluster 2 and Cluster 3. This pattern suggests that they either belong to highly competent but disengaged profiles or they exhibit stronger cognitive engagement despite a possible lack of motivation. However, due to the small sample size of this group (n = 2), it is difficult to draw strong conclusions.

In contrast, students from vocational secondary education are overwhelmingly represented in Cluster 2, the low-performing, externally motivated group. This suggests that they may struggle with statistical competence and require external incentives to engage with data. Their underrepresentation in the other clusters implies that they are less likely to demonstrate intrinsic motivation or confidence in their statistical abilities. This finding is consistent with previous research indicating that students from vocational backgrounds may have had less exposure to advanced mathematical and statistical concepts during their prior education, which can influence their confidence and willingness to engage with data-driven decision-making.

These findings suggest that prior education plays a role in shaping student teachers' engagement with data use, particularly in terms of statistical competence and motivation.

However, the chi-square test revealed that 50.0% of the expected counts were below 5, with a minimum expected count of 0.24, which may limit the statistical robustness of these associations. This means that while patterns can be observed, caution is needed in interpreting the results, as the small sample sizes in some groups may affect the reliability of the conclusions.

A Kruskal–Wallis test was conducted to determine whether clusters differed significantly in terms of academic performance (average score in the last exam period) and mathematics hours per week in secondary education. The test for academic performance yielded $H(3) = 0.109$, $p = 0.991$, indicating that the clusters did not significantly differ in their average scores from the last examination session. The test for weekly mathematics hours resulted in $H(3) = 5.292$, $p = 0.152$, showing no statistically significant differences, though a slight trend suggested potential variation between clusters. Since neither test reached statistical significance ($p > 0.05$), the results indicate that the differences in the profiles of student teachers were not directly influenced by academic performance or exposure to mathematics in secondary education.

Lastly, we examined whether gender was associated with cluster membership using a chi-square test. The analysis revealed no statistically significant association between gender and cluster membership, $\chi^2(6, N = 147) = 5.40$, $p = 0.493$. Thus, gender did not appear to play a systematic role in shaping the identified profiles. It should be noted that some cells had low expected counts, which may limit the reliability of the test results.

6. Discussion and Implications

The findings of this study reveal a complex interplay between motivation, attitudes, and academic self-concept in shaping student teachers' engagement with data use. While most student teachers recognize the importance of data in education, their affective engagement remains significantly lower than their cognitive awareness, highlighting a key barrier to meaningful DBDM. Additionally, distinct student teacher profiles emerge, showing substantial variation in statistical competence, motivation, and emotional responses to data.

6.1. Discussion of the Main Findings

The pre- and post-test results regarding academic self-concept further indicate that targeted interventions, such as an e-course on basic statistical concepts, can effectively enhance self-estimated competence in underdeveloped areas. However, these gains are not uniform, as some student teachers adjust their confidence downwards after exposure to more advanced statistical concepts, reflecting a shift from overconfidence to a more calibrated self-assessment. These findings raise important questions about how teacher education programs can foster not only competence but also sustained motivation and emotional engagement with data use.

6.1.1. Motivation and Attitudes of Student Teachers Toward Data Use

An insight from this study is that the motivation for data use among student teachers is often externally driven, with many engaging with data due to institutional requirements rather than personal conviction. This reliance on controlled motivation aligns with Self-Determination Theory (Deci & Ryan, 2000), which suggests that when engagement is fueled by external pressures rather than internalized values, long-term adoption remains fragile. While this pattern has also been observed among in-service teachers (Vanlommel et al., 2016), the underlying reasons may differ between student teachers and experienced teachers. For student teachers, a lack of authentic classroom experience may contribute to their external orientation toward data use. Unlike experienced teachers, who often have a concrete pedagogical context in which to apply data insights, student teachers primarily encounter data through coursework and training exercises. This may result in a perception of data use as an abstract, administrative task rather than a valuable tool for instructional decision-making. In contrast, research suggests that experienced teachers who develop a sense of ownership over their classroom data are more likely to engage with it in meaningful ways (Datnow & Hubbard, 2016). The absence of such direct classroom responsibility among student teachers could explain why their engagement with data remains more superficial and driven by external expectations, rather than intrinsic motivation.

Beyond motivation, this study highlights that student teachers exhibit a stark contrast between cognitive and affective attitudes toward data use. While they generally recognize the importance of data in education and acknowledge its potential benefits (high cognitive attitudes), their affective engagement remains low, indicating limited emotional connection to data. This suggests that even when student teachers understand the relevance of data on an intellectual level, they may not feel comfortable or confident about using it in practice. The discrepancy between cognitive and affective attitudes is a crucial finding, as prior research has shown that attitudes—particularly affective ones—play a key role in determining whether teachers actively engage with data or avoid it (Vanhoof et al., 2014). A possible explanation for this low affective engagement is that student teachers may feel overwhelmed by, or anxious about, data use, particularly if they lack prior exposure to working with real educational data. Experienced teachers, on the other hand, have had more opportunities to develop fluency with data over time, which may lead to greater comfort and willingness to engage with it. Furthermore, the context in which teachers use data matters—while in-service teachers typically work with real student performance data, including standardized assessment results, student teachers often engage with data in hypothetical, decontextualized scenarios. This lack of real-world applicability may hinder the development of a sense of ownership and confidence in working with data.

Regarding data literacy and how student teachers perceive data use, the results show that the category 'observations of students' is marked highest as data that can be used, namely by 97.5% of the student teachers. In addition, when asked about the relevance of the different kinds of data, 'conversations with students' has the highest mean. When asked for what data can be used, teachers report, to a large extent, that they differentiate within their class. This might imply that student teachers primarily view data as a tool to tailor their instructional methods to meet the diverse needs of their students. Differentiation involves modifying teaching strategies, learning activities, and assessments to accommodate varying student abilities, learning styles, and interests (Tomlinson, 2000).

6.1.2. Academic Self-Concept of Student Teachers

The study highlights the role of academic self-concept in shaping student teachers' perceptions of data use. Unlike in-service teachers, who develop their self-concept through direct experience with student data in the classroom, student teachers' self-perceived competence is primarily shaped by their prior education, statistical training, and theoretical exposure to data use. Their confidence in handling data is therefore based on self-estimation rather than actual application, making it a more fluid and potentially unstable construct at this stage of their professional development.

The findings show that student teachers generally rate their competence in basic statistical concepts positively, particularly in areas such as mean, median, and data visualization. However, their self-concept is notably lower for more complex statistical elements, such as box plot interpretation. This suggests that while they may feel comfortable with fundamental statistical tasks, their confidence decreases when faced with less familiar or more advanced data representations. This pattern aligns with research indicating that academic self-concept is domain-specific and tends to fluctuate in response to perceived difficulty levels and prior exposure (Eccles & Wigfield, 2002; Marsh et al., 2017).

A key question is how this self-perceived competence will translate into actual data engagement once student teachers enter the teaching profession. Since they have not yet had the opportunity to apply their statistical knowledge in real classroom settings, there is a risk that their confidence may not align with their actual ability to use data effectively for instructional decision-making. Previous research suggests that novice teachers often experience a decline in self-efficacy when transitioning from teacher education to the classroom, as they encounter the complexity of real-world teaching situations (Chang et al., 2022). Similarly, student teachers who currently rate their statistical competence highly may struggle to apply their knowledge effectively when faced with real student data and the pressures of decision-making in the classroom.

Moreover, this study suggests that student teachers' self-concept may be shaped more by their familiarity with statistical concepts than by their ability to interpret assessment data for educational purposes. In contrast, experienced teachers often develop their confidence in data use through ongoing exposure to school-based data, such as standardized assessment results, formative evaluations, and tracking students' progress (Mandinach & Gummer, 2016). Student teachers, however, primarily engage with abstract statistical exercises rather than authentic classroom data, which may limit their ability to connect their self-perceived competence with practical data-informed decision-making. This could explain why some student teachers, despite rating their statistical skills positively, still exhibit low affective engagement with data use.

6.1.3. Student Teacher Profiles

This study identified four distinct student teacher profiles regarding data use, revealing substantial variation in how future educators might engage with data. These findings underscore the multidimensional nature of data literacy, suggesting that statistical competence alone is insufficient to foster meaningful and sustained data engagement. Instead, motivation, attitudes, and self-concept play a crucial role in determining whether student teachers perceive data use as a valuable tool for educational decision-making or as an external obligation.

The first and fourth clusters represent student teachers with strong statistical competence but low emotional engagement. While these individuals possess the technical skills needed to analyze data, their lack of intrinsic motivation and affective connection to data use presents a major challenge. Prior research suggests that individuals who lack emotional investment in a subject are less likely to apply their knowledge in meaningful ways (Sanbonmatsu & Fazio, 1990). For these student teachers, merely strengthening their statistical literacy will not be sufficient to ensure that they actively engage with data in their teaching careers. A key question is whether their disengagement stems from a lack of pedagogical context for applying data—since student teachers often work with abstract data rather than real classroom cases—or from a perceived disconnect between data use and the human aspects of teaching. Without targeted interventions that highlight the practical and student-centered benefits of data use, this group risks viewing data as an administrative burden rather than a pedagogical resource.

The second cluster, composed of student teachers who struggle with statistical competence, but maintain a relatively positive attitude toward data use, presents an entirely different challenge. Unlike Clusters 1 and 4, these student teachers may be motivated to engage with data but lack the necessary skills to do so confidently. This group is disproportionately represented by students from vocational education, suggesting that prior exposure to mathematical and statistical reasoning may play a role in shaping data confidence. While these student teachers do not reject data use outright, their low self-concept in statistical abilities may act as a barrier to meaningful engagement. Research on self-efficacy suggests that individuals who lack confidence in their abilities are more likely to avoid tasks that involve those skills, even when they recognize their importance (Eccles & Wigfield, 2002). Traditional statistics courses may be particularly ineffective for this group if they reinforce feelings of incompetence, rather than providing structured, scaffolded learning experiences that gradually build confidence in data interpretation.

The third cluster represents student teachers who engage with data primarily due to external pressures, rather than personal conviction. These student teachers may recognize the necessity of data use in the profession, but do not yet see it as an intrinsic part of their teaching identity. This aligns with Self-Determination Theory (Deci & Ryan, 2000), which suggests that externally motivated behaviors are less likely to persist over time unless individuals internalize their value. The challenge for this group is to transition from compliance-driven engagement to authentic, meaningful data use. If student teachers view data use as merely another requirement imposed by educational authorities, they may struggle with long-term engagement and deep learning (Vansteenkiste et al., 2007). Providing student teachers with opportunities to work with real student data, reflect on its implications, and connect data use to their own teaching philosophy could help shift motivation from external to more internalized regulation.

This divergence highlights an important conceptual distinction between cognitive understanding and emotional engagement. While cognitive attitudes reflect a rational appreciation of the value and relevance of data for instructional purposes, emotional engagement refers to how comfortable, confident, or enthusiastic individuals feel when interacting with data. Prior research suggests that affective responses often play a stronger role in shaping actual behavior than cognitive beliefs alone (Sanbonmatsu & Fazio, 1990). In this study, student teachers' limited emotional engagement—even among those who recognize the importance of data use—may hinder their practical application of data-informed teaching. Addressing this emotional component is therefore essential when designing professional development interventions that aim to build not only competence, but also confidence and motivation for data use.

A key finding of this study is that prior education significantly influences cluster membership. Students from vocational education were over-represented in the low-performing, externally motivated cluster, while those from general and technical education were more evenly distributed across the higher competence groups. This suggests that students enter teacher education with varying levels of exposure to data literacy, which in turn shapes their attitudes, motivation, and self-concept regarding data use. However, interestingly, gender, academic performance and prior mathematics exposure did not significantly differentiate clusters. This finding challenges the assumption that stronger general academic achievement automatically translates into higher engagement with data use. Instead, factors such as prior exposure to educational data, attitudes toward quantitative reasoning, and the perceived relevance of data for teaching likely play a more decisive role.

6.2. Implications for Practice

The findings of this study highlight the necessity for teacher education programs to move beyond a purely technical approach to data-based decision-making (DBDM). While statistical competence is crucial, it does not automatically translate into meaningful engagement with data in instructional decision-making. Addressing motivation, attitudes, and self-concept is essential to ensure that student teachers not only understand how to use data but also feel confident and motivated to integrate it into their practice. This requires a more holistic approach to data literacy, one that integrates cognitive, affective, and contextual factors throughout teacher preparation.

A key implication is the need to foster intrinsic motivation for data use, particularly among student teachers who often engage with data due to external pressures rather than personal conviction. According to Self-Determination Theory (SDT), fostering the three basic psychological needs—autonomy, competence, and relatedness—is key to promoting the internalization of motivation and encouraging more autonomous engagement with data use (Deci & Ryan, 2000). Unlike in-service teachers, who experience direct accountability for their students' learning outcomes, student teachers typically lack immediate responsibility for applying data in a real classroom context. As a result, they may perceive data use as a theoretical or administrative task, rather than a meaningful instructional tool. Teacher education programs can address this by creating learning environments that explicitly support the internalization of motivation. Embedding data-use activities within pedagogically relevant contexts, providing choice and autonomy in data-related assignments, and fostering collaborative learning can all contribute to building a more self-determined orientation toward data use.

To bridge the gap between data use as a technical skill and as a practical instructional tool, teacher education programs should emphasize its relevance to real-world teaching. For experienced teachers, this connection often develops organically through classroom observations, formative assessments, and tracking of student progress over time. In contrast, student teachers must rely on indirect or simulated experiences, which can make data feel less relevant to their future practice. Embedding data use within authentic teaching scenarios is therefore critical. Rather than presenting it as an isolated skill, training should integrate data use with broader pedagogical goals and classroom decision-making processes. Practicum placements offer a valuable opportunity in this regard. When scaffolded data-related tasks are embedded into practicum experiences, student teachers can engage with authentic student data under the guidance of experienced mentors. These experiences allow student teachers to explore the practical implications of data use, gradually build competence and confidence, and develop a sense of ownership over data-driven instructional practices. Within coursework, activities such as case studies, reflective assignments, and practice-based projects can further support authentic engagement. Simulated student performance analyses, collaborative data-driven lesson planning, and guided interpretation of assessment results provide concrete opportunities for student teachers to experience how data informs teaching. By explicitly linking these activities to instructional decision-making and student learning, teacher education programs can help student teachers recognize that data are a valuable tool for improving educational outcomes—not merely a bureaucratic requirement. Moreover, the motivational profiles identified in this study suggest the need for differentiated support strategies. For example, student teachers in Cluster 4 ("Highly Competent but Disengaged Analysts")—who exhibit strong statistical competence but low emotional investment—may benefit from collaborative, reflective activities that make data use more socially and pedagogically meaningful, such as co-teaching lessons based on assessments. Those in Cluster 2 ("Low-Performing, Externally Driven Users") could be supported through scaffolded, low-stakes practice with feedback data during practicum placements, where mentor teachers model the instructional value of data. Students in Cluster 3 ("Moderate Performers with External Motivation") might gain from structured peer group discussions that emphasize shared decision-making based on data, helping them internalize the relevance of these practices. By tailoring interventions to the needs of different profiles, teacher education programs can more effectively foster both competence and autonomous motivation for sustainable data use.

Emotional barriers to data use represent another important area for attention. Many student teachers experience discomfort or anxiety when working with data, often due to limited prior exposure and a lack of real classroom context in which to apply their statistical knowledge. Unlike experienced teachers, who gradually build confidence through repeated interactions with student data, student teachers may feel overwhelmed by unfamiliar data formats, complex interpretations, or the perceived pressure to make instructional decisions based on data. To prevent disengagement, teacher education programs must create supportive learning environments that normalize mistakes, encourage a growth mindset, and build confidence in data interpretation over time. Scaffolded experiences that gradually increase in complexity can help student teachers develop fluency in working with data. Structured peer discussions, guided reflection, and mentorship from experienced teachers provide additional support. Working with real but low-stakes student data, discussing misconceptions in a collaborative setting, and receiving targeted feedback on data interpretation can foster both competence and emotional resilience. It is essential that data use is framed as a tool for exploration and instructional improvement rather than an evaluative measure of teaching ability. When student teachers understand that engaging with data is a learning process, and that mistakes are part of that process, they are more likely to persist and develop a positive, sustainable relationship with data-driven decision-making.

Developing lasting data literacy requires a sustained, integrated approach across the teacher education curriculum and into early career teaching. Isolated courses on statistics or assessment interpretation are insufficient for building deep and transferable data-use competencies. Instead, data use should be embedded across multiple courses and field experiences, with explicit connections to instructional practice and student learning outcomes. Standardized assessment data presents a particular challenge. While experienced teachers frequently interact with such data, student teachers often lack opportunities to engage with real standardized test results in a meaningful way. Without such experiences, they may struggle to see the relevance of standardized data, leading to disengagement or scepticism about its role in education. Teacher education programs should address this by exposing student teachers to authentic standardized assessment data, guiding them through its interpretation, and encouraging critical reflection on its pedagogical implications. Discussions on the appropriate and ethical use of standardized assessments can further deepen understanding and promote critical engagement with data. Moreover, longitudinal support is crucial. Once student teachers enter the profession, their interactions with standardized assessment results shift from hypothetical analysis to real-world application. Continued mentorship and professional development opportunities during the early years of teaching can help new teachers refine their data-use skills, build confidence, and translate data insights into effective instructional decisions.

Finally, it is important to recognize that student teachers vary in their readiness and attitudes toward data use. A one-size-fits-all approach to data-use training is unlikely to be effective. Some student teachers possess strong statistical skills but remain disengaged due to negative attitudes or low motivation, while others are highly motivated but lack competence. Differentiated instruction, tailored support, and collaborative learning experiences can help ensure that all student teachers develop both the skills and confidence needed to work with data effectively. By adopting a comprehensive approach that addresses cognitive, affective, and contextual dimensions of data literacy, teacher education programs can better prepare student teachers to engage with data in meaningful, sustainable ways. This, in turn, can contribute to more effective, data-informed instruction and improved student outcomes in the long term.

6.3. Limitations

Several limitations of this study should be acknowledged. First, the study relied exclusively on self-reported data, which introduces potential biases related to social desirability, subjective interpretation of constructs such as motivation and attitudes, and possible over- or underestimation of one's competence. Second, while the study focused on student teachers' individual perceptions and experiences, it offered limited consideration of the broader educational and institutional contexts in which these individuals are situated. Factors such as institutional culture, mentor teacher support, and school-level expectations may substantially influence student teachers' engagement with data and should be explored in future research. Third, the subgroup analyses based on cluster membership and prior education background included relatively low cell counts in some categories (e.g., students from vocational or arts education), which may limit the robustness and reliability of comparisons involving these groups. Another limitation concerns the measurement of attitudes toward data use, which was conducted only after the intervention. As a result, the study cannot provide evidence regarding whether, or to what extent, the e-course may have influenced student teachers' affective dispositions toward data use. Fourth, the generalizability of the findings is constrained by the specific national and institutional context of Flemish teacher education in which the study was conducted. Caution should therefore be exercised in extending these results to other educational systems or cultural contexts. Addressing these limitations in future studies may further enhance our understanding of how student teachers engage with data use across diverse settings. Finally, while the survey used in this study was based on items adapted from validated scales, the overall instrument—as adapted and translated into Dutch—has not been formally validated as an integrated survey. The reliability of the individual scales was assessed through Cronbach's alpha, but the instrument as a whole should be interpreted with caution, and future studies should consider conducting a full validation process for use in this context.

6.4. Future Research

While this study provides valuable insights into the role of motivation, attitudes, and academic self-concept in shaping student teachers' engagement with data use, several areas warrant further investigation. One possibility for future research is to examine the long-term impact of data literacy training on actual classroom practices. This study focused on student teachers during their training, but it remains unclear whether their engagement with data persists or changes once they enter the profession. Longitudinal studies following early-career teachers could provide insights into how motivation and confidence evolve over time, and what factors support or hinder sustained data use.

Another critical area for exploration is the effectiveness of different instructional approaches in fostering data literacy. While this study suggests that hands-on, practice-based learning experiences may enhance motivation, further research could test empirically which pedagogical strategies—such as case-based learning, mentorship, or reflective practice—are most effective in bridging the gap between knowledge and application.

Additionally, future research should explore how school culture and professional environments shape teachers' motivation and attitudes toward data. While teacher education lays the foundation for data literacy, the extent to which teachers continue to use data depends on the support structures within their schools.

Finally, as Artificial Intelligence (AI) tools are increasingly integrated into educational contexts, future research could investigate how such technologies might influence teachers' development of data literacy and their interaction with educational data. While this was beyond the scope of the present study, it represents an important area for further exploration.

7. General Conclusions

This study provides insights into student teachers' motivation, attitudes, and academic self-concept regarding the use of data. The identification of four distinct motivational and competence-based profiles highlights that student teachers do not engage with data use in a uniform way. These profiles—ranging from highly competent but emotionally detached users to low-performing but externally motivated individuals—underscore the need for differentiated support within teacher education. The observed increase in perceived competence following the e-course further demonstrates the potential of targeted interventions to strengthen data literacy. The findings also highlight the relevance of Self-Determination Theory in understanding how motivation shapes student teachers' engagement with data use and suggest that fostering autonomous motivation should be a priority. Practically, teacher education programs can enhance student teachers' data literacy by providing scaffolded, low-stakes opportunities to work with authentic data—both within coursework and during practicum placements—while addressing basic psychological needs. Tailoring these learning experiences to the diverse motivational and competence profiles of student teachers may foster more sustainable and meaningful engagement with data-informed teaching. Future research should further explore how emerging technologies and contextual factors influence student teachers' data literacy development and motivation for data use.

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Abbreviations

The following abbreviations are used in this manuscript:

DBDM	Data-based decision-making

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