Transforming Education Excellence in Ethiopian Higher Learning: Unleashing the Power of Digital Innovation to Drive Data-Informed Decision-Making

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***Abstract*—Data-driven decision-making is being increasingly adopted worldwide to improve the quality, accessibility, and equity of education. However, there is limited empirical evidence regarding its implementation in developing countries such as Ethiopia. This study aims to investigate the practice of data-driven decision-making in Ethiopian higher education institutions to improve education quality. The study utilized purposive and simple random sampling techniques. Two public universities in Ethiopia were selected based on purposive sampling techniques. 98 faculty members and 211 students and 16 stakeholder participants were selected based on simple random and purposive sampling techniques. The results reveal a lack of genuine data-driven decision-making practices, limited knowledge and awareness of data analytics, reliance on manual analysis and basic software, and a lack of training and support systems for data utilization. The study recommends that leaders collaborate with external organizations, provide training on data usage, prioritize investments in data analytics, and develop policies for data management and decision-making. Future research should investigate the awareness and readiness of top institutional leaders regarding data-centric education and its impact on education quality. The findings of this research will contribute to improving the quality of education in higher education institutions by promoting data-driven decision-making.**

***Keywords*—data-driven decision-making, data analytics, higher education, developing country**

I. INTRODUCTION

Data-Driven Decision-Making (DDDM) has been playing a substantial role in modern education, since it includes the systemic collection, analysis, and utilization of various data from multiple sources to inform a wide range of decisions to improve student and school success [1]. In the practice of DDDM, data analytics plays a crucial role. It involves the use of techniques and tools to analyse large amounts of data from different sources to facilitate and enhance the decision-making process [2]. Data has become an essential tool in driving progress and is now seen as a crucial component of the worldwide development agenda, often called the "data revolution" [3]. As Segueda *et al*. [4] further emphasizes, data is essential for directing and regulating educational systems in all countries. The study by Schildkamp [5] suggest that educational institutions everywhere should use data to track their performance, identify areas for development, and make data-driven decisions that effectively and efficiently raise the standard of instruction. Particularly considering the magnitude and confidentiality of the data that Higher Education Institutions (HEIs) manage, DDDM is essential [6]. It is widely believed that using data for decision-making is a global initiative to transform education [7]. Additionally, there is a growing demand worldwide for educational systems to base their strategic planning and decision-making on evidence [8]. Thus, there is a global shift towards a more data-driven culture [9]. Vatsala *et al*. [10] state that DDDM has the potential to foster a more collaborative and transparent culture among higher education stakeholders; with the help of IT, this culture is even more advanced.

However, in spite of the efforts made by African governments, the education sector continues to face challenges related to accessibility, quality and inequality, a situation is evident in Ethiopia [11]. The Internet economy plays a pivotal part in Africa' s growth. Despite a negative macroeconomic outlook due partly to COVID-19, Google and the International Finance Institution (IFI) estimate that Africa' s digital economy has the potential to contribute $180 billion to its GDP by 2025. With more than 120 million populations [12], Ethiopia has countless challenges that require serious initiatives to devise innovative solutions to problems in a fast-changing world. Accordingly, the Ethiopian government exerts efforts to improve education quality by incorporating digital solutions. However, Ethiopian HEIs lag behind other developing countries HEIs in adopting DDDM. Developing countries such South Africa, Kenya, and Ghana implemented DDDM in their HEIs to improve different educational activities with robust data infrastructure and collaboration with private institutions. Whereas, the Ethiopian HEIs face challenges such as lack of funding, limited infrastructure and lack of data literacy in education. Among the many developing countries who adopted DDDM, for instance, south African universities such as University of Pretoria, University of Cape Town ... implemented learning analytics improved student success, teaching-learning process and resolved disparities in education in South Africa [9]. Controversial, the Ethiopia' s HEIs practices basic digitization rather than advanced DDDM.

While DDDM does not serve as a comprehensive solution to the challenges faced by higher education and student learning, it offers valuable opportunities. As it is indicated in this paper, DDDM offer some benefits. However, some scholars argue that implementing DDDM may be misused,

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resulting in unintended consequences or the neglect of critical aspects of teaching and learning. This drawback may stem from data quality issues, such as the use of incomplete or outdated information, which can lead to misguided strategies [13] and the potential for bias. For example, data might be utilized solely for accountability purposes [14], thereby overlooking opportunities to enhance teaching and learning outcomes. Additionally, data security and privacy concerns may arise. If the data is not safeguarded by robust security measures, it could result in data breaches that pose significant risks [13]. In summary, integrating DDDM into the education system has its drawbacks, much like any educational technology that is not implemented and managed systematically and strategically.

Whereas, DDDM can contribute to resolving some problems such educational, economic and cultural in developing nations. DDDM can assist in achieving objectives like as personalized learning, evidence-based instruction, institutional efficiency, and ongoing innovation [15]. In general, DDDM best practices in higher education can ensure effective management and utilization of institutional data for quality education and maximizing its impact. Since high-quality graduates are expected to enter the workforce from higher education, it is crucial that the educational environment be flexible enough to accommodate the upcoming practices. Furthermore, it is the institution' s responsibility to efficiently manage and utilize the enormous amount of data generated within and outside the institution. All this contributes to the transition of higher education from traditional to more contemporary methods.

Despite its role in addressing educational quality, access, and disparity issues, evidence about the educational use of DDDM in developing countries is limited. Many prior studies such as [15–17] have concentrated on DDDM in higher education in developed nations, but its prevalence and effectiveness in developing countries remain uncertain. The research conducted by Schildkamp, Poortman, and Sahlberg [18] revealed that limited information is available regarding data use, also known as DDDM, in developing countries. Similarly, Amakyi' s [19] study on DDDM in education in Ghana emphasized the need for further investigation into the impact of DDDM on education. The process of using data is more complicated, context-specific, and less rational than a simple linear model [20, 21]. In addition, assessing the current DDDM practices in HEIs can inform context-specific strategies to improve education quality, accessibility and other institutional activities by executing DDDM while focusing inadequacies of human capacity, processes, tools and technologies. Moreover, educational data-based decision-making is getting high value in the Western countries than the developing ones. To the best of the researchers' knowledge, there has been no related study that has particularly examined the practice of DDDM using a conceptual framework in Ethiopian higher education institutions. As a result, this study contributes to the literature by establishing and implementing a novel conceptual framework to identify crucial elements influencing DDDM implementation in HEIs. Therefore, employing an original conceptual framework exploring DDDM practices can assist educational stakeholders in effectively implementing strategies that enhance the quality of education in developing countries. According to Alzafari and Kratizer [22] "embedding quality into higher education institutions is a challenging matter given the complexity of the higher education environment". Moreover, education requires new ways of thinking, doing, evaluating, and demonstrating impact [23]. Therefore, to contribute to the transformation of higher education, it is timely and necessary to conduct research examining DDDM practice.

Several stakeholders are involved in the DDDM process in higher education institutions. These stakeholders include: lecturers (academic staffs), IT professionals, Institutional researchers, students, administrators, management, industry partners, and external academics [24–26].

For this study, faculty members, including deans, department heads, department coordinators, lecturers, library professionals, ICT professionals, registrar experts, students, and education program relevance and quality enhancement office directors, are selected as DDDM stakeholders considering Ethiopian higher education institutions DDDM practice.

The purpose of the study is to investigate the practice of DDDM to improve the quality of education in higher education institutions in Ethiopia. To establish a systematic approach for making assessments on DDDM practices, a conceptual framework was developed. This framework also facilitates a comprehensive understanding of the subject under investigation. As noted by Walden University [27], it is common for a single theory to be insufficient in fully addressing the phenomena under study. However, there are several frameworks for implementing DDDM in education, including those developed by [1] from the Rand Corporation, [28], and a conceptual framework proposed by [29].

A conceptual framework of factors that contributes to effective implementation of DDDM was created using pertinent literature to analyze the implementation of DDDM in HEIs in Ethiopia. To develop our conceptual framework, we created terms and searched on open access databases for our predefined key terms. Furthermore, we examined websites and research papers from internationally recognised organisations working on the transformation of higher education, such as Educause and the Rand Corporation, which conduct studies on evidence-based decision-making. Following a thorough assessment and analysis of the current literature, we developed our conceptual framework to assess the practice of DDDM in HEIs in Ethiopia. The framework comprises six key categories and numerous subcategories, as presented below. These categories include data (technical) infrastructure, analytical capability, a culture of data-informed decision-making, involvement of institutional research, policy considerations, and resource investment, drawing from pre-existing literature. These six categories were chosen based on their theoretical alignment to the DDDM in HEIs and their relevance to our research questions. Afterward, we evaluated these components based on qualitative and quantitative data collected from a diverse group of research participants in Ethiopian public universities.

II. Conceptual Framework

This framework comprises six major factors (Fig. 1.) that contribute to the effective implementation of DDDM in

HEIs.

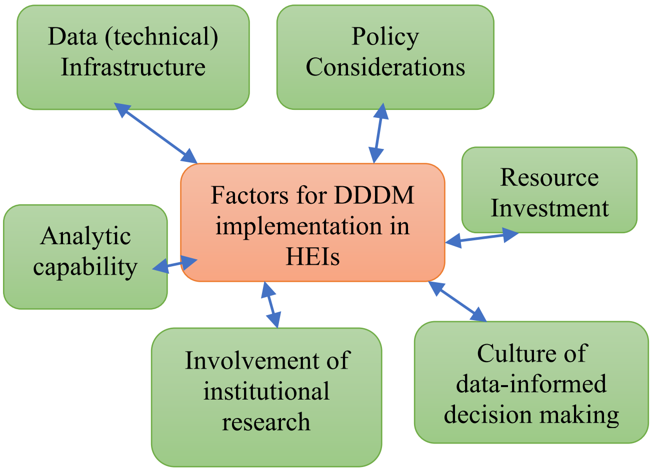

Fig. 1. Factors for DDDM implementation in HEIs.

A. Data (Technical) Infrastructure

Among the many components that help in the effective implementation of DDDM, data infrastructure is at the forefront. Dahlstrom [24] indicated that the backbone of data management is a robust infrastructure that encompasses cutting-edge analytics tools and the ability to store, organize, and analyse data with ease. These are the building blocks that enable institutions to run and manage their IT services and environments smoothly. To fully gain the rewards of DDDM, having a solid foundation of data infrastructure and technology is essential. Gill *et al*. [29] indicated that, it' s not just about having access to this infrastructure; it' s also about constantly improving and upgrading it to keep up with the ever-evolving technological landscape. In situations where there exists a significant volume of unstructured data that surpasses the capabilities of conventional database software, it becomes imperative to implement complementary systems to provide adequate support. The contemporary approach to handling vast quantities of data involves the application of advanced technological tools such as NoSQL databases, Hadoop software for parallel processing, and Gephi software for analysing social networks [30]. To keep these cutting-edge, data-driven technologies up and running, a certain level of know-how is an absolute must.

Research conducted by New [13] suggested that an education system effectively guided by data would rely on various educational technologies aimed at utilizing data to improve every facet of the education system, such as the, learning management system, data warehouse, and student information system.

1) Student information systems

Student Information Systems (SISs) serve as a comprehensive platform for the management of student-related data, including but not limited to admission, enrolment, and registration processes, fee management, attendance record keeping, test and exam administration, certificate and document management, as well as program and course management [31, 32]. They are designed to keep track of important records. Various options are available for Student Information Systems (SISs), including both proprietary and open-source alternatives. The SIS system is integrated with multiple data systems and is used to generate valuable insights that can aid in making informed decisions.

2) Learning management system

The Learning Management System (LMS) is an important tool for modern education, providing a dynamic platform that empowers data-driven learning. The learning management software package is designed to assist in the delivery of learning materials, resources, and activities, as well as to manage administrative tasks. LMSs are web-based software platforms that offer an interactive online learning environment. They also automate the administration, organization, delivery, and reporting of educational content and student outcomes [33]. LMS tools let students and parents communicate outside of the classroom. These tools make it easier to collaborate and communicate effectively. LMS systems provide personalized teaching, learning, and support. Both proprietary and open-source LMSs exist. A study by New [15] indicated LMS integrates with SIS and other data systems to support informed decision-making and increase student achievement

3) Data warehouse

Kumar [34] indicated that data warehouses play a crucial role in facilitating data-driven education by providing a centralized repository for all the data from various sources, including student information systems, learning management systems, and other systems such as administrative records. In general, a "data warehouse is a repository (a collection of resources that can be accessed to retrieve information) of an organization' s electronically stored data, designed to facilitate reporting and analysis" [35]. Furthermore, in data-driven decision-making, it is crucial to use technology-based procedures to analyze data and provide practical insights to decision-makers. In doing this, Business Intelligence (BI) tools assist in BI processes. They are commonly used to analyze and present data [36]. Data-driven decision-making presents analysis results in user-friendly formats like reports, dashboards, graphs, and charts. DDDM uses data visualization tools like dashboards to provide decision-makers with quick access to key measures and trends through a graphical user interface, aiding in decision-making [37].

B. Analytics Capacity

Analytics capacity refers to the ability to conduct analysis and employ technology to examine data to identify patterns and address issues. While traditional human interpretation of data outcomes can be utilized for analytics, contemporary automated methods, such as educational data mining techniques, can also be employed [38]. The study by Dahlstrom [24] posits that the willingness to utilize data for decision-making is the foundation of analytics capacity. To ensure the effectiveness of the decision-making process, it is imperative to establish in-house technical assistance systems that can aid decision-makers, including teachers and department heads, in utilizing data [29]. When an institution lacks the internal capacity to handle certain activities, seeking external technical assistance collaboration may enhance the outcomes of data analytics [29, 39]. To improve the analytical capabilities of organizations, it is recommended that training programs be implemented with a focus on data utilization, accessibility, analytics, and tools for personnel at all levels. This approach can effectively increase the individual capacity of staff to access and utilize data [24, 29]. It is also important to address practice-related concerns such as data standardization and accuracy, as noted by [24]. To establish a truly data-driven education system, it is vital to prioritize enhancing institutional data accessibility, which has been emphasized as the initial step by UNESCO [40]. Enhancing institutional data accessibility for educators and other stakeholders can be achieved by implementing a data governance plan [39]. This approach also facilitates the improvement of analytics capacity, which can be further augmented through self-service tools such as dashboards and portals [24]. As a result, an institution' s analytics capability will continue to mature, progressing from a mere willingness to use data, building capacity and collaborating with external data-intensive organizations.

C. Culture of Data-Driven Decision-Making

A DDDM culture values the use of data and analytics to gather insightful knowledge that can lead to advancements. It focuses on using evidence-based data to make decisions rather than using intuition. According to Ross [41], certain data-driven initiatives may fail due to a lack of a culture that prioritizes data-based decision-making. To establish a culture of data-driven decision-making, it is essential to have dedicated leadership and accountability systems in place [24, 29, 39]. To build a strong DDDM organizational culture, it is important to have a clear vision and plan for data utilization, promote data sharing, allocate sufficient time and resources for data activities, and encourage participation in data conferences [29].

D. Policies

According to Roux [42], "Public policy refers to a proposed course of action of government, or guidelines to follow to reach goals and objectives, and is continuously subject to the effects of environmental change and influence." To effectively incorporate DDDM in HEIs, it is crucial to establish policies that support data collection, access, and utilization, as well as data analytics [24, 29, 39].

E. Institutional Research Involvement

The act of utilizing data to inform decision-making is a cooperative endeavor. Therefore, establishing an analytics program aimed at improving decision-making throughout an organization necessitates a collaborative approach both internally and externally [24, 39]. Among the required collaboration between different stakeholders, the interaction between IT and Institutional Research (IR) is necessarily acquired [24]. As a result, the institutions have to develop good strategies and initiatives to promote data usage and analytics through research and collaboration between IT, IR, and other stakeholders. Moreover, to truly unlock the potential of big data and turn it into actionable insights, it' s crucial that the business objectives behind the analytics communicated to the technical team [43]. To be successful in the realm of DDDM, one must harness the power of both internal and external collaborations.

F. Investment/Resources

To enhance educational institutions' analytical capacity, it is crucial to allocate resources and invest in staffing capacity [24]. Specifically, to transition towards a data-driven education system, studies recommended investing in talent (human resources), technology, and tools [39]. For instance, Webber and Zheng [39] emphasize the importance of investing in technology such as business intelligence platforms and visualization tools in their study.

III. Potential Barriers and Facilitators for the Implementation of DDDM

The implementation of DDDM in higher education can be influenced by several barriers and facilitators.

Barriers: The adoption of DDDM in HEIs can be hindered by several barriers including data quality issues, privacy/security concerns and lack of data literacy [44], inadequate tools (lack of data infrastructure), organizational culture, a lack of collaboration [45, 46] and lack of budget and skilled human capacity [47]. In sum, several barriers related with people, processes, technology and culture hamper individual' s ability using data effectively.

Facilitators: There are several factors that facilitate the implementation of DDDM in HEIs. According Webber and Zheng [39] for effective execution of data analytics in DDDM having facilitators related with people, processes, technology and culture facilitate the implementation of DDDM. Among them the availability of good leadership support to adoption/integration, capacity or data literacy in using advanced analytic tools, good data governance policies that ensure data quality and accessibility facilitate the implementation of DDDM [29, 24]. In different view, committed leader and support can address both cultural and technological barriers [43], this indicates good leadership can address several discussed barriers and hence it facilitates the effective implementation DDDM.

IV. Study Objectives

The main objective of this research was to scrutinize the present application of DDDM in the teaching and learning activities of HEIs in Ethiopia. In particular, the study aimed to address the following research questions (RQs):

RQ1: How are educational data analysis techniques, policies and practices integrated into teaching and learning activities within HEIs in Ethiopia to improve the quality of education?

RQ2: What kind of support is provided to higher education faculty members and ICT specialists by these institutions for data usage and data-informed decision-making? At the end, the ultimate purpose of this study is to inform HEIs and national policymakers to establish data-related policies concerning collection, usage, sharing, and data-driven decision-making to improve education quality.

V. Materials and Methods

A descriptive study was conducted among higher education faculty members, stakeholders and students to evaluate the current practice of DDDM within a specific framework in institutions of higher education in Ethiopia.

A. Participants

DDDM relies on sophisticated analytics technologies and our study aims to assess this sophisticated technology' s current practices in HEIs in Ethiopia. Accordingly, in order to meet our research objective, we have utilized both purposive and simple random sampling techniques. Therefore, the HEIs were selected based on purposive sampling techniques, that have expected to relying on advanced educational technologies better than the rest of remaining universities in the country. To select participants simple random and purposive sampling techniques were employed. To realise an equilibrium between generalizability and in-depth understanding we employed both simple random sampling and purposive sampling to select our participants. Moreover, simple random sampling leads to higher validity and overcome the potential limit of purposive sampling generalizability.

Accordingly, two public universities were selected purposefully for the study. Both institutions are distinguished, first-generation universities in Ethiopia, selected for their extensive student and faculty populations as well as their advanced ICT infrastructure compared to newer universities [48]. Due to the resource constraints and aim to in-depth inquires two universities one from urban and one from rural were only considered for this study. Thus, the data collected from this strategically chosen universities reveals the critical DDDM practices limitations that might represent the universities at the country. In Ethiopia, universities are categorized by their founding years: the first-generation dates back before 2007, the second generation emerged in 2007, the third generation in 2011, and the fourth generation established in 2016 [49].

Four departments, namely Computer Science, Information Science, Software Engineering, and Information Technology, from the Faculty of Computing and Informatics, were selected with the aim of leveraging ICT in teaching and learning activities. The four departments mentioned above were selected for their better data infrastructure utilization compared to the others. To ensure the representative and unbiased selection of students, simple random selection techniques are employed, and purposive sampling is employed to target stakeholders who have a direct influence or knowledge of DDDM or educational technologies in the selected institutions. The sampling included 129 instructors and 447 graduating undergraduate students from the Faculty of Computing and Informatics. Out of 129 faculty members, 98 instructors were selected as sampling units, and out of 447 students, 211 were chosen using simple random sampling technique. The sample size was determined using Kothari [50] sample size determination formula. The selection was made by generating random numbers from two lists containing 129 instructors and 447 graduating undergraduate students. Additionally, 14 experts were selected consisting of ten ICT specialists and four registrar experts. Moreover, four library officials, and two education program relevance and quality enhancement office directors were selected purposely. All the individuals purposely chosen to participate in this study occupy leadership roles within their respective Higher Education Institutions (HEIs). For instance, team leaders and directors from two universities include library officials and education program relevance and quality enhancement office directors, were tasked with addressing education quality matters. Similarly, library officials were chosen to supply data on educational technologies within the library system. Finally, directors from the Office of Education Program Relevance and Quality Enhancement were selected to provide data on the actual implementation of data-driven decision-making.

B. Instrumentation

We collected data from diverse group of participants with different data collection instruments (i.e. questionnaire, interview and observations). The questionnaire was given more priority, followed by the interview. Whereas the observations were used as a fulfilment and cross-checking for the reliability of data collected through the other instruments.

1) Questionnaire

This study employed a self-developed questionnaire designed based on a literature review through a systematic process to ensure validity and reliability. A research objective was defined to target key concepts in the study, such as DDDM, data analytics and support services provided to stakeholders to improve DDDM, with questions tailored to stakeholders with direct influence on DDDM practice. A mix of open ended and closed ended questions were developed using neutral language to minimize bias. The questionnaire was organized into five parts: querying data use, data (technical) infrastructure, provided support services, data analytics, and DDDM practices. Most of the questions were open-ended to allow for detailed responses. Data was gathered through a questionnaire administered to faculty members, ICT specialists, registrar experts, and students. Due to the unique job roles and responsibilities of the participants within their academic institutions, as well as their involvement in DDDM, the surveys varied. The research team (BF, DA and WJ) and two data science specialists reviewed the questionnaire to ensure its content validity. Additionally, a pilot test was conducted to establish the reliability and validity of the questionnaire before the actual data collection at a first-generation university which was not included in the sample study. The survey was piloted with faculty members, including the faculty dean, department head, department coordinator, and four instructors from each department (computer science, information science, software engineering, and information technology). Furthermore, two students from each department, two ICT specialists, two registrar experts, two library experts and two education program relevance and quality enhancement experts participated in the pilot study. The Cronbach' s alpha method was used to examine the instruments' dependability, and the instruments' reliability score was 0.91 across its 20-item Likert scale (1= Strongly Disagree to 5= Strongly Agree). Specific items focused on five core domains.: *(1) Data use* (e.g. My university uses automated technologies to collect and process structured data (e.g. enrollment records). (2). *Data infrastructure* (e.g. My university have a centralized data repository (e.g. data warehouse or cloud-based platform and faculty members and staff have access to students' full data. (3). *Data analytics* (e.g. My department uses predictive analysis to identify at-risk students. (4.) *support services* (e.g. Training is provided to faculty members and staff on intelligent data analytics tools (e.g. Tableau/Power BI). (5). *DDDM practice* (e.g. Decisions about academic help (e.g., tutoring) are guided by insights from data-driven analysis. Reliability test results close to one indicate high reliability of the instruments. Feedback on the clarity and ease of completing the survey was obtained and used to modify the questions accordingly. The questionnaire was distributed to participants via email and direct in-person interaction. The questionnaires used in this study are included as supplementary file S1 for reference.

2) Interview

In order to have deep understanding of the current practices of DDDM we conducted detailed semi-structured interviews with two directors from the universities' education program relevance and quality enhancement office and four senior library officials. The interview was conducted in English at two universities by the researchers and was recorded using a Sony audio recorder. The interview data was then transcribed, analysed, interpreted, and the results were reported. The interview guiding questions are provided as supplementary file S2 for reference.

3) Observations

Furthermore, observations of technical data infrastructure were done to examine the nature and availability of support for data-driven decision-making. According to Creswell [51], observations involve the researcher taking detailed field notes on the behaviour and interactions of people in the research setting. These field notes encompass recording data management practices, data systems, and educational technologies in general as observed in universities. The observation of data management-related activities necessitates the collection of evidence in a natural setting. This approach, particularly in the context of existing educational technologies, provided the researchers with a wealth of valuable information. An important advantage of conducting observations is the ability to simultaneously view multiple components. The researcher, identified as ZA, who possesses work experience as an expert in data systems, had the opportunity to observe and analyse the existing data systems, including hardware and software, as well as the interconnections and functionality of the entire data system in universities in great detail. Therefore, this technique was utilized to gather information that cannot be obtained through other methods and to verify the reliability of data collected through other instruments. The data was collected between February 7, 2023, and March 16, 2023.

C. Data Analysis

The collected data were subjected to analysis employing both qualitative and quantitative methodologies. Thematic analysis was used to analyse the qualitative data, which involved several steps. Firstly, the data was systematically arranged and processed through the transcription of interviews, documentation of field notes, and subsequent categorization according to the respective sources of information. Secondly, the data was thoroughly checked to gain a general understanding of it. Thirdly, coding was used to categorize data with similar meanings by labelling each data unit with a code that symbolizes or summarizes the meaning of the extracted information. The formation of basic themes was conducted deductively using a theory-driven framework as a guide to define categories [52]. The developed themes were narrated, and the data was subsequently interpreted. Finally, the findings of the study were compared with the information from relevant theories and literature. Descriptive statistics were used to analyse the quantitative data, which involved determining the frequencies and percentages necessary to answer certain questions in the questionnaire. The integration of data from both qualitative and quantitative methods was achieved in the results and discussion sections of the study.

To maintain confidentiality in reporting, the institutions in question denoted as university 1 and University 2. At the time, participants distinguished by the initial three letters of their names followed by numerical values. For instance, "ICT" was used to denote information and communication technology specialists, "Ins" for instructors, "Stu" for students, and "Lib" for librarian.

D. Ethical Considerations

To conduct this study, ethical approval was obtained from the institutional ethical review board of [X] University Institute of Technology, [x] University. All ethical considerations were taken care of while collecting the data and reporting the results.

VI. Result and Discussion

A. Result

The questionnaires were distributed to different stakeholders including faculty members (n = 98) and undergraduate graduating class students (n = 211), who were selected based on the sample size determination formula. Additionally, the questionnaire was also distributed to fourteen participants, including ICT specialists (n = 10) and registrar experts (n = 4). A total of 298 individuals (i.e. 91 faculty members, 194 students, 9 ICT specialists and 4 registrar experts) completed the questionnaire, resulting in a response rate of 92.44%.

Among the surveyed instructors, 2 individuals possess less than 5 years of experience, while 34 (37.36%) have accumulated between 5 and 8 years of experience. Additionally, 23 (25.27%) instructors have garnered between 9 and 12 years of experience, and 32 (35.16%) have more than 12 years of experience. Similarly, the ICT professionals included in the survey have held roles involving data-intensive tasks. Out of the 9 ICT specialists, 2 (22.22%) have less than five years of experience, 3 (33.33%) have 5-8 years of experience, and 4 (44.44%) have 9-12 years of experience.

The vast majority of educators, accounting for 87.91% (n = 80), held a Master' s degree, while 12.08% (n = 11) possessed a Doctoral degree. The majority (89%) of the participants (educators) taught undergraduate students. Among the interviewed (n = 6), 2 held a doctoral degree, 2 contained a master' s degree, and 2 held a bachelor' s degree. Participants from the ICT Directorate had experience in data system management, application development and teaching and learning technologies. The next section of this paper presents the main findings of the study.

1) Data-driven educational technologies and practices

Results of the current study indicate that there were a lot of in-house developed, customized, open source, and unintegrated systems (Table 1) that are used for different institutional purposes. Among them, student information systems (student registration systems) and e-learning platforms (Moodle and Blackboard) can be mentioned.

Table 1. Some of the educational technologies in use by the HEIs in Ethiopia

Educational technologies	Developed by
Student Registrar System (SRS)	In-house developed
Integrated Student Information Management system	
Research Management System	
Online Examination System	
One e-card System	
e-Learning platform (Moodle)	Customized by a local company
DSpace	Open source

The results of the study reveal that educational institutions frequently rely on fragmented in-house systems, such as student registration platforms, to facilitate processes such as enrollment and grade submission. These systems are obligatory for both educators and students and have demonstrated efficacy. The majority of participants indicated that they use the Moodle Learning Management System (LMS), but a significant portion did not use any LMS at all. Although LMSs were employed during the COVID-19 outbreak, their usefulness is being questioned. The institutions lack intelligent analytic tools, data warehouses, and techniques for handling vast amounts of data, including social media data, which is used for educational purposes.

The results indicate that educational institutions were not effective in utilizing student behavioural and parental information to improve student achievement, except for student demographic and assessment-related data. The majority of ICT expert (77.77%, $n = 7$) were not familiar with the benefits of a data warehouse. Many participants reported that their institutions are deficient in a culture of using data for informed decision-making. There seemed to be no clear vision or strategy for implementing data-driven decision-making. Furthermore, there are no established policies for data collecting, processing, quality managing, accessing, sharing, or data-driven decision-making, except for open access in some institutions and research data sharing in university 1. To offer a comprehensive comprehension of the importance of Information and Communication Technology (ICT) in the context of higher education in Ethiopia, the perspectives of respondents from diverse groups are presented in Table 2.

Table 2. Respondent' s opinion on the role of ICT in education at Ethiopian HEIs

Respondents	Examples of Quotations
Stu6	"I know, not all tasks were improved as a result of IT but the registrar and related tasks improved and the data accessibility as well."
Ins19	"Accessing student data is easier now and no need to go to registrar to request it. It is easily accessible from SRS. Also, providing materials, such as handouts, to students has improved a lot due to ICT. Sharing teaching materials is also possible."
ICT7	"ICT doesn' t have big role besides keeping and storing the data safe."

In addition, the interview response from directors of the Education Program Relevance and Quality Enhancement Office indicated that ICT in their institution is providing basic services such library cataloguing, registration and grade reporting but not engaged in using advanced data analytics or DDDM. One of the interviewees noted the following.

"…in our university, using ICT, we are providing courses via video conference, making decisions based on data from the student registration system, and using ICT for classroom activities."

The findings indicate ICT is playing its role in providing basic services than advanced data analytics activities.

2) Data analysis techniques

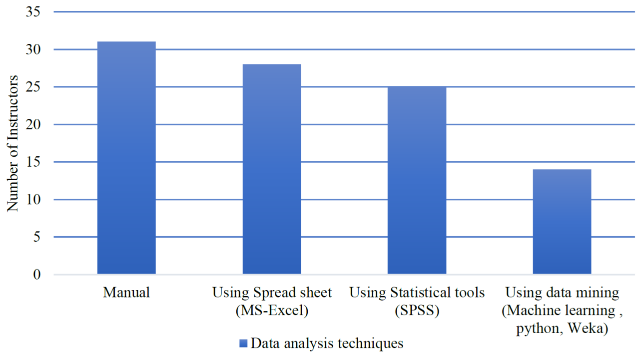

Fig. 2. Data analysis tools employed by Instructors.

As the above Fig. 2 indicates, a significant portion of instructors (34%, $n = 31$) manually analysed data, while 30.76% ($n = 28$) used basic software like Microsoft Excel. The result also indicated that the majority of instructors, 46.15% ($n = 42$) respondents, employed descriptive analysis, whereas the minority of instructors, 6.59% ($n = 6$), performed diagnostic analysis in their teaching and learning activities. The following Fig. 3 provides an overview of the data analysis methods used.

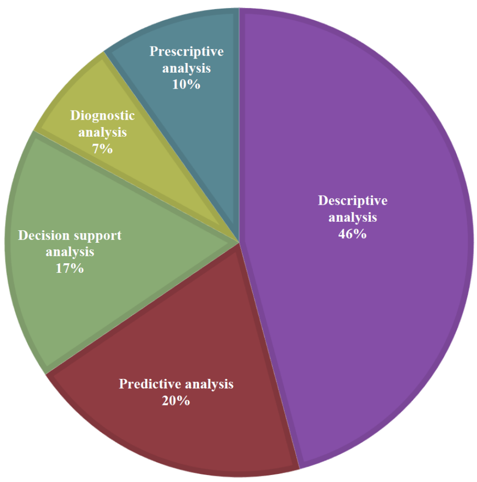

Fig. 3. Instructors' experience in data analysis types.

The study' s findings also indicate that IT professionals have no experience handling unstructured data, including data from social media. The IT specialist lacks experience with unstructured data due to HEIs' lack of engagement in data analysis and lack of provided training on unstructured data. Table 3 shows some of our respondent' s opinions on data analytics capability in their respective higher education institutions. The respondents were denoted by the initial three letters of their names and the corresponding numerical values (i.e. "ICT" denotes for Information and Communication Technology specialist and "Ins" denotes Instructor or faculty member).

Table 3. Respondent' s opinion on data analytics capability in Ethiopian HEIs

Themes	Examples of Quotations
Big data (unstructured data) managing skill	ICT3: "Our university manages structured data using an application like MSSQL, MYSQL…from my own experiences. I have not yet tried to handle unstructured data for big data analysis.
Professional development	Ins4: "No training has been given to use data-driven decision-making and making it a culture."
Intelligent tools	Ins22: "Even our SRS does not include any intelligent analysis which provides feedback for our students."
Data analytic tool	Ins4: "No application available to help me to do DDDM."
Culture of data use	Ins68: "Our institution ICT provides infrastructure and different ways of capturing data from different stakeholders in the university. However, there is no way of using this data for decision making."
Data analysis	Ins91: "… I manually observe the data and make decisions."
Data accessibility	ICT3: "Students can easily register easily than ever, instructors can easily submit an assessment and the system will automatically calculate and map it to a predefined and maintainable set of grades, staff evaluation made online are some."
Data analysis culture	Ins19: "… no culture of analyzing data and using the result for decision making."
Willingness to use DDDM	Ins7: "I believe, with the awareness being created and the available technology, data-driven decision-making will improve in the future."

The themes outlined in Table 3 were categorized within the overarching theme of "data analytics capability". Each of these themes has the potential to contribute to the effective execution of DDDM in higher education. For example, the ability to manage diverse types of data, encompassing both structured and unstructured data. Structured data is inherently organized and defined, such as product names and user IDs, while unstructured data is typically stored in native formats, including data from social media posts, emails, images, and audio/video files. Therefore, possessing the capability to manage both structured and unstructured data in higher education aids in the implementation of DDDM. However, the responses from the participants indicated a lack of awareness and experience in managing unstructured data in Ethiopian higher education institutions.

Regarding data analytics tools, the responses from the participants indicated the absence of intelligent data analytics tools available to support educational stakeholders, such as instructors, in performing various teaching and learning data tasks. Additionally, the respondents noted a deficiency in a data analytics culture, which is essential for enhancing DDDM in higher education. Conversely, the respondents highlighted an improvement in data accessibility in registrar activities through the use of various systems. Furthermore, the willingness of respondents to implement DDDM in Higher Education Institutions (HEIs) in Ethiopia may expedite the implementation process.

3) Support services provided to educational stakeholders in higher education institutions

The majority of the respondents (80 %, $n = 80$) (instructors and ICT specialists) indicated that no efforts have been made to provide professional training in data analytics or to develop data analytics support systems. There was also no formal training given on data usage, data analytics, data tools, or data-driven decision-making. No initiatives promoting this practice exist within these institutions, and no collaboration with external organizations or universities focusing on data utilization has been established. Data from the interview with directors of the Education Program Relevance and Quality Enhancement Office indicated that stakeholders did not receive any training in data analytics or DDDM. In contrast, the institutions have partners who collaborate to innovate their library systems. The respondents indicated the need for good strategies and initiatives to promote data usage and analytics through research and collaboration between IT and institutional research and other stakeholders. Furthermore, the vast majority of the respondents (93.33%, $n = 93$) (Instructors and ICT specialists) felt that their institutions do not have leadership advocating for data-driven decision-making. The results of the interviews with the majority of directors from education program relevance and quality enhancement offices also indicated that their institutions do not have leadership advocating for DDDM. However, a little higher than half of the respondents (53.07%, $n = 57$), Instructors, ICT specialists, and registrar experts strongly agreed that their institutions were willing to allocate resources and make substantial investments in improving digital infrastructure. Likewise, the findings from interviews with participants, such as library officials and leaders of the Office for Education Program Relevance and Quality Enhancement, strongly advocate that their individual institutions were willing to invest resources in enhancing the digital infrastructure for registrar and library operations.

In summary, the interview findings indicate a lack of activities promoting DDDM and a similar absence of genuine DDDM practices in Ethiopian HLEs. The findings from surveys and observations also confirm the same results as the interviews. The following section presents the further analysis of the results.

B. Discussion

The empirical evidence collected from our diverse participants was well-supported by the proposed framework. The study' s findings reveal that truly data-driven decision-making is yet to be implemented in Ethiopian higher education institutions. Our results support Blaich and Wise [53] study that reported that data-driven decision-making is not yet widely practiced in higher education, despite the growing importance of data use and the need for accountability. Among the essential components that help to build a data-driven education system, the data warehouse does not exist and works with several disconnected systems. Moreover, there were no integrated intelligent data analytics tools that supported the stakeholders in making the best decisions. Major results of the study are discussed below:

1) Data (technical) infrastructure usage

The findings of the research indicate that a variety of in-house-developed, customized, open-source and unintegrated systems are being employed for diverse purposes across the institutions. The results from the interview also indicate that Ethiopian HEIs have many systems that support teaching and learning activities, including virtual systems. The findings from the survey indicates there is an improvement in registrar activities. Similarly, the interview with the directors of the Office of Education Program Relevance and Quality Enhancement indicates an improvement in registrar activities. The respondents expressed the student information systems

(Student registration systems) in the institutions were effective due to the settled accountability. As indicated by our initial findings [54] and subsequently corroborated by our extensive research, these systems are crucial for both educators and learners, demonstrating their efficacy. Our result is also supported by a previous study conducted in Ethiopia [55], which also showed that software products in the registrars of Ethiopian universities are being used (essentially for registration and grading) better than the other departments in universities. Moreover, we triangulated that the majority of students, 75.77% (n = 147), responded that their institution' s registrar activities, especially registration and grading, were improved due to SRS. While the learning management systems were not utilized effectively to enhance student outcomes because there might be no settled accountability measure. In contrary, the university of Cape Town in South Africa uses LMS to maintain continuity and educational outcomes [56]. The institutions lack accountability systems for improving student outcomes and education quality using LMS. Our finding is supported by a study of Dahlstrom *et al*. [57] that reported that the majority of faculty do not take advantage of advanced LMS capabilities that have the potential to improve student outcomes. This might imply a lack of awareness of leadership on the potential capability of LMS in improving student outcomes and leading to a data-driven education system. The study by Assefa [55] also showed that most of the managers and leaders of the university are ignorant or lack awareness of the importance of using software products in Ethiopian universities. The study by Bervell & Umar [58] reports that most African educators have little knowledge of or interest in using LMSs.

Whereas, except for the unavailability of data warehouses and data analytics assistance tools, universities have a lot of data infrastructure, especially data centers, high-capacity servers with large storage capacity, cloud service, and network infrastructure. Having a standard database designed to support data storage and retrieval is not enough to make data-driven education. Rather, data warehouses, specialized systems designed to facilitate analysis by aggregating multiple data sources, are the foundation of data-driven education [15]. However, the institutions have a lot of standalone disconnected systems and activities, controversial of having connected and designed by leaders to strive for comprehensive solutions and processes that lead institutions to a more mature position for data analytics [39]. The experience of designing and developing software later with analytics training might help create assistance tools for data analytics and promising for the future. One of our respondents, Lib2, a library senior expert from university 1, expressed the status of data utilization in his university: "In the 21st century, data is the new oil. We Ethiopians have not yet utilized our own real oil, and now we are also not using the new oil, i.e. data. We have a lot of fragmented systems that are designed for specific applications. I believe it is time for us to have a holistic view and use the new oil with integrated systems." The data collected from various respondents through surveys also confirms the librarian' s opinion mentioned above. For instance, Stu6 expressed his opinion on the digitalization of his university, stating, "I know not all tasks were improved as a result of IT, but the registrar and related tasks improved, and the data accessibility as well." Similarly, an instructor (faculty member) identified as Ins19 expressed his opinion, saying, "Accessing student data is easier now, and there' s no need to go to the registrar to request it." It is easily accessible from SRS. Furthermore, the provision of materials, such as handouts, to students has significantly improved as a result of ICT. Sharing teaching materials is also possible. Finally, the ICT specialist, denoted as ICT7, expressed the entire university ICT system as having a limited role, stating, "ICT doesn't have a big role besides keeping and storing the data safe."

C. Analytic Capacity

Our findings also indicated that except for the library system experience of using research performance analytics tools at the institution level, there is no indicative initiative and plan to integrate intelligent technical assistance data analytic tools and pieces of training to promote data analytics at all. The finding from the interview also indicates there are no activities performed to use intelligent analytics systems. We also noticed that, apart from collaborating with partners who work to innovate library systems, the institutions were not cooperating with any organizations focusing on data use and analytics to improve data-driven decision-making. Unlikely, the South African University of Cape Town partnered with private techno companies such as Microsoft [56] and Stellenbosch University collaborated with SAS Institute [59] to improve DDDM in HEIs. The findings of the study indicate no utilization and support services were provided to the faculty members and ICT specialists. Studies showed that school leaders who possess a deep understanding and unwavering dedication to utilizing data as a tool for decision-making can construct a strong vision for data utilization within their educational institutions [60, 61]). The respondents also expressed their institution collects and store a lot of data in different ways, with no systemic and strategic implementation of data analytics; this was also confirmed in the previous studies [23, 39]. The majority of the faculty members analyze their data manually or using Microsoft Excel. Previously, similar results in the country about data analysis practices were also reported by Akal *et al*. [62]. The IT professionals also have no experience of handling unstructured data, including data from social media. In general, educational institutions considered in this study are far from the practices of true data analysis using intelligent data analytics tools. This might call for increased awareness and collaboration of all stakeholders to find a workable solution.

D. Culture of Data-Driven Decision-Making

To establish a culture of data-driven decision-making in an education system, it is essential to have dedicated leadership and accountability systems in place. The vast majority of the respondents (93.33%, n = 93) (Instructors and ICT specialists) felt that their institutions did not have a leadership advocating for data-driven decision-making. The interviews with some of the directors of the Office of Education Program Relevance and Quality Enhancement also indicated similar results. A significant portion of participants stated that there was no culture of data use for making informed decisions in their institutions. The results indicate that there is no clear vision or plan for integrating data-driven decision-making. Moreover, the institutions lacked clear policies on data collection, use, and sharing, including data-driven decision-making policy. This shows that either the leaders are unaware of data-driven decision-making and its impact on education quality, or they are ignorant of informed decision-making. In addition, the reason may be the lack of a clear vision, plan, and policy. The Global Partnership for Education has indicated that Ethiopia lacks a well-defined strategy or established procedures to effectively manage educational information systems at an operational level [63]. In one way or another, the study of Taye and Teshome [64] shows that Ethiopia, at a country level, does not have a comprehensive data protection and privacy law. Studies like Siemens *et al*. [23] reveal the lack of focus on policy and strategies is hindering the adoption and deployment of learning analytics (i.e., analytics type).

E. Investment/Resources

Regarding investment in analytics, the results reveal that no investment was made to produce skilled human resources in analytics or the technologies needed for performing data-driven decision-making. In their interviews, several directors from the Office of Education Program Relevance and Quality Enhancement stated that institutions had not invested any resources, either human or technological, towards implementing DDDM. In contrast, the respondents agree that their institution will be voluntarily to invest in the data (technical) infrastructure. Similarly, the results of interviews with library officials indicate that the universities are willing to invest in ICT infrastructure. This result aligns with our finding that there was an improvement in library and registrar activities in higher education institutions through digital infrastructure, as discussed in previous sections of this paper. Previously, studies also indicate that the Ethiopian government was not only willing to transform higher education via ICT but also engaged in increased investment in ICT [49]. However, the ICT infrastructure was underutilized [64–66]. As the necessity of technical devices, the leaders committed to decision-making based on educational data are also essential for any effort for planning and implementation of data analytics projects in institutions [67].

F. Technology Based Solutions for DDDM

As discussed somewhere in this study in a truly DDDM process in higher education a lot of technological tools, systems and techniques are integrated to have the advantage of DDDM. For instance, LMS, SIS, data warehouse, BI tools, dash boards and data visualization tools are implemented to process DDDM.

Moreover, the process of DDDM in higher education can be enhanced by the integration of Artificial Intelligence (AI) in the process. AI is the technology of the moment and AI can help in collecting, processing and analysing and personalizing a huge amount of digital data accumulated in higher education and help HEIs to make better informed decisions [68]. For instance, HEIs can employ AI based predictive analytics to identify at-risk students. In sum, AI systems are helpful to identify individual learning needs and experiences, make data-driven decisions and allocate resources more effectively [69]. For instance, the integration of AI in the education sector in India is enhancing personalized learning, supporting teachers and improving administrative processes [70]. Furthermore, AI-powered solutions have been effectively adopted at Georgia State University and Purdue University, where predictive analytics enable educators to assist with at-risk students. Georgia State' s AI-powered advising system, which monitors over 800 risk variables, has resulted in an 18% increase in student retention rates after its deployment [71]. In another way, the United Arab Emirates (UAE) has set a goal of being a global leader in AI by 2031, with a significant commitment to AI adoption in important sectors including education [72]. In general, due to the significant benefits of incorporating AI into education, countries such as India have launched a statewide self-paced learning project known as "AI for All" [73]. Thus, for better data-driven decision making the utilization of AI in DDDM processes help in various dimension of higher education decision making activities.

VII. Conclusion and Recommendations

In this study, we have presented evidence on the practices of data-driven decision-making to improve the quality of education in higher education institutions in Ethiopia. Through a comprehensive review of the existing literature, we have constructed a conceptual framework that encompasses several categories, including technical data infrastructure, analytical capabilities, the culture of DDDM, the engagement of institutional research, policy considerations, and resource investment. The conceptual framework we proposed received substantial support from the evidence generated in our study. The results of this research suggest that genuine data-driven decision-making practices are lacking in Ethiopian higher education institutions. Despite the increased recognition of building an advanced data warehouse platform as a prerequisite for sophisticated analytics, the findings indicate a lack of knowledge and awareness concerning the use of data analytics and intelligent tools for implementing data-driven decision-making to enhance educational quality. There is an apparent need for visionary leaders in higher education institutions who understand the value and application of data, particularly data analytics.

One lesson drawn from this study is that higher learning institutions in developing nations, such as Ethiopia, need to learn from universities that have advanced data-driven education systems and collaborate work towards advancing higher education through information technology. Another lesson is that higher education institutions need to prioritize the development of skilled professionals in data analytics and advancing data analytics technologies. The successful integration of data-driven decision-making for quality education depends not only on the willingness and awareness of leaders but also on the knowledge and expertise of ICT and other professionals skilled in intelligent data analytics technology. This study provides a significant contribution to practical approaches by prioritizing activities for implementing data-driven decision-making in an educational setting. Additionally, this research provides valuable insights for other institutions to assess their current practices and introduce essential improvements.

In light of these findings, the following short-term and long-term strategies are recommended.

A. Short-Term Strategies

- It is recommended that data-related policies concerning collection, usage, sharing, and data-driven decision-making be established at institutional and national levels.
- Implement well-planned and organized data literacy training programs for all stakeholders, covering data collection, analysis, interpretation, and visualization.
- Establish inter-institutional collaborations with foreign organizations or academic institutions that possess practical, cutting-edge DDDM expertise.
- Launch a DDDM pilot project at the class, department, or faculty level, and progressively expanding over time.

B. Long-Term Strategies

- Invest in data analytics technologies and tools and implement DDDM at the institutional level.

C. Limitations of the Study

The study employed purposive sampling to select sample universities and some of our participants, which may limit the generalizability of our findings. However, the findings can be generalized with some limitations beyond the selected universities. The use of convenience or purposeful sampling methods introduces the potential for bias in the sample. However, our study gathered data from two universities located in different natural settings (urban vs. rural) and diverse groups of participants who were also randomly selected. While this study aimed to collect useful insights into the current practices of DDDM in Ethiopian HEIs, it is important to acknowledge the potential of response bias from the survey, which could affect the validity of the findings. However, to minimize the bias, we used neutral language in our questions. We believe this could not resolve fully, and hence the results should be interpreted with care. Lastly, we believe this study will not only uncover differences in implementing procedures but also improve current practices of data-driven decision-making. This is crucial for stakeholders to set directions and implement strategies under DDDM guidelines and regulations

D. Future Research Recommendations

Future research should explore the awareness of data-centric education among institutional leaders and its potential impact on education quality. In addition, future research should look into barriers and facilitators to DDDM adoption at the national level, with a particular focus on organizational barriers. Furthermore, future studies should examine the role of Ethiopian educational policymakers and governmental agencies in facilitating DDDM adoption.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Zelalem Asfaw conceived the research idea, designed the study framework, developed the research instrument, collected the data, conducted data analysis and interpretation, and prepared the draft of the manuscript. In addition, he reviewed, edited, and finalized the manuscript. Abu Santure supported the study by contributing to data analysis and reviewed final version. Daniel Alemneh, Worku Jimma, and Bekalu Ferede provided academic supervision throughout the research process, critically reviewed the manuscript, contributed to revisions, and approved the final version for publication. All authors had approved the final version.

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