Implementing Data-Driven Decision-Making to Improve the Quality of Education in Ethiopian Higher Learning Institutions

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Abstract

This paper investigates the barriers and facilitators to the adoption of data-driven decision-making (DDDM) in higher education institutions (HEIs) in Ethiopia. The study employed a three-round modified Delphi method involving a panel of experts comprising of faculty members and specialists in Information and Communication Technology (ICT). A total of 57 experts participated, and 39 barriers and 20 facilitators were identified. The top three barriers included the lack of a data-driven decision-making policy, organisational culture, and a data management policy. The availability of network infrastructure was identified as the most important facilitator. The results of the study indicate that organisational barriers are important factors in the effective implementation of data-driven decision-making to improve the quality of education in Ethiopian higher education institutions. The findings emphasise the significance of policy in overcoming obstacles and promoting a culture of data-driven decision-making in Ethiopian higher education institutions. Improved policy and effective implementation of practices can address the identified barriers.

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Key words: data-driven decision-making, barriers, facilitators, education quality, Ethiopia

Résumé: Cet article étudie les obstacles et les facteurs facilitant l'adoption de la prise de décision fondée sur les données DDDM dans les établissements d'enseignement supérieur (EES) en Éthiopie. L'étude a utilisé une méthode Delphi modifiée à trois tours, impliquant un panel d'experts composé de membres du corps enseignant et de spécialistes des technologies de l'information et de la communication (TIC). Au total, 57 experts ont participé à l'étude, et ont permis d'identifier 39 obstacles et 20 facteurs de facilitation. Les trois principaux obstacles sont l'absence de politique de prise de décision fondée sur les données, de culture organisationnelle et de politique de gestion des données. La disponibilité d'une infrastructure de réseau a été identifiée comme le facilitateur le plus important. Les résultats de l'étude indiquent que les barrières organisationnelles sont des facteurs importants dans la mise en œuvre efficace de décisions basées sur les données et visant l'amelioration de la qualité de l'éducation dans les établissements d'enseignement supérieur éthiopiens. Les résultats soulignent l'importance de la politique pour surmonter les obstacles et promouvoir une culture de prise de décision fondée sur les données dans les établissements d'enseignement supérieur éthiopiens. Une politique améliorée et une mise en œuvre efficace des pratiques peuvent permettre de lever les obstacles identifiés.

Mots clés: prise de décision fondée sur les données, obstacles, facilitateurs, qualité de l'éducation, Éthiopie

Introduction

Ensuring high-quality education is a critical concern, especially given the growing demand for proficient individuals in light of technological advancements and economic growth (Baitanayeva et al., 2020). According to Saidy (2020), ensuring the quality of higher education poses a critical challenge to the world at large, but even more so for Africa. Previous studies by Sultana et al. (2009) indicate that the key factors influencing the quality of higher education are the calibre of faculty, curriculum standards, technological resources, research atmosphere, accreditation procedures, administrative guidelines, funding, assessment, and effective governance.

Saidy's (2020) research indicates African higher education quality is influenced by institutional factors such as governmental control and the institutional set-up of higher education systems, limited resources and capacity building, limited research and limited publication, cultural and

contextual relevance, and faculty qualification, as well as individual factors such as faculty orientation towards student-centred approaches to learning, leadership, and good governance.

More specifically, Shabani et al. (2014) highlighted a decrease in per-unit expenses, a notable rise in student enrolments, substandard academic quality of admitted students, deficient academic and research facilities such as libraries and laboratories, insufficient training of teaching staff, inadequate governance, limited effectiveness of quality assurance systems, the lack of quality assurance bodies to establish and enforce quality standards, and the absence of mechanisms to uphold quality factors as key contributors to the deterioration of higher education standards in Africa. Similarly, the quality of higher education in Ethiopia is impacted by both internal and external factors that contribute to a decline in educational standards. Among them are lack of a positive learning environment, insufficient library facilities and low student attendance, student misbehaviour, and political interference (Ibido, 2020). According to Oliso (2023), the quality of higher education is impacted by the insufficient supply of educational resources like ICT, libraries, laboratories, and a shortage of experienced educators.

According to UNESCO (2023), education in developed countries is of higher quality and is aided by modern technologies. In developing nations, the standard of education is low and is impacted by different factors such as the socioeconomic circumstances of students and institutional elements (Fomba et al., 2022). In order to improve education quality in developing countries, there is a need for better quality teaching, and teaching tools are crucial (Heyneman, 1983). Additionally, Gray Group International (GGI) Insights (2024) proposed several tactics to enhance the quality of education. These include investing in teacher training and development, encouraging innovation and the integration of technology in classrooms, and boosting student engagement and motivation. In a more elaborated way, GGI Insights (2024, "Strategies") identified nine strategies for improving education quality. These are: "providing training to teachers and professional development; providing access to high-quality teaching materials and resources; creating a positive and inclusive learning environment; personalizing learning experiences to meet individual student needs; implementing technology in the classroom to enhance learning; encouraging parental involvement and engagement; incorporating project-based learning and hands-on activities; developing strong assessment and evaluation processes; and prioritizing mental health and well-being in education."

Among the many reasons identified for decline in education quality, failure to incorporate evidence-based decision-making, which ensures strong fundamentals, also has a detrimental impact on the quality of education (Bustillo & Patrinos, 2023). In order to enhance educational quality, the implementation of data-driven decision-making systems (data use) has been proposed (Schildkamp, 2019). To obtain advantages like personalised learning, effective management, resource allocation, and, in general, student and institutional improvement, the execution of DDDM, which is an advanced technology for the education system, is essential. In the realm of higher education institutions (HEIs), the utilisation of data-driven decision-making processes facilitated by data analytics tools has been shown to be instrumental in various aspects. These include the identification of students at risk of dropping out, as well as the reduction of dropout rates (Mukred et al., 2020). Furthermore, such tools have been employed to enhance feedback mechanisms (Star & Collette, 2010), pinpoint effective teaching methods (Sclater et al., 2016), monitor student engagement levels, and forecast student success (Sclater et al., 2016; Robinson et al., 2016). Additionally, the application of data analytics in HEIs has been linked to improvements in student success rates and graduation rates (West et al., 2018), as well as in the enhancement of HEI evaluation outcomes (Sclater, 2014). Moreover, by establishing realistic objectives to address inefficiencies and combat declining student enrolment figures, HEIs can strategically navigate challenges (Unifyed, 2016), ultimately leading to more informed decision-making processes, improved institutional performance, and heightened student accomplishments (Gaftandzhieva et al., 2023). Data-driven decision making (DDDM) involves the systematic gathering and scrutiny of various types of data by educators, school leaders, and administrators, encompassing input, process, outcome, and satisfaction data (Marsh et al., 2006). This information is utilized to inform a variety of decisions aimed at enhancing student and institutional success (Marsh et al., 2006). Scholars comprehensively describe DDDM as 'data use' (Schildkamp, 2019). In the DDDM educational system, various stakeholders, including teachers, institutional leaders, administrators, students, parents, and government entities, will play a crucial role in collecting, processing, and utilising the results of data analysis.

The use of DDDM in education has become increasingly popular for improving the quality, accessibility, and inequalities in the field. American Universities like Arizona State University and Concordia University Wisconsin, have successfully utilized analytics to enhance students' academic experience and achieve higher graduation rates. For instance, Tacoma in the USA implemented predictive analytics and saw a 27.6% increase in the high school graduation rate (New, 2016). In addition,

Arizona State University is also utilising analytics to enhance students' academic experience and has achieved a 20% increase in graduation rates. Concordia University Wisconsin (CUW) has also effectively implemented an analytics program to identify at-risk students, resulting in an 82% student retention rate, a 10% increase within one year (Attaran et al., 2018). Similarly, universities in Europe and South Africa have also embraced DDDM and witnessed positive outcomes in education quality (Lemmens & Henn, 2017) and Europe (Nouri et al., 2019). Studies indicate DDDM is used not only to enhance education quality but also to resolve education accessibility and equity issues in the education sector.

Despite the role of DDDM in improving educational practices, its implementation faces several challenges and barriers. These include issues like data literacy in education, in which educators need to have the expertise and ability to convert data into usable information that can be applied in the classroom (Terrill, 2018), inadequate tools, a lack of collaboration, insufficient leadership support and commitment, organisational culture (Bolhuis et al., 2016; Schildkamp et al., 2016), and associated costs and a lack of skilled human capacity around the issue of DDDM (Chui, 2016). The study by Schildkamp et al. (2016, p. 244) grouped factors promoting and hindering DDDM in educational institutions as: "organizational characteristics (i.e., vision and norms, leadership, support, and collaboration), data characteristics (i.e., accessibility of timely data, usability and quality of the data), and user characteristics (i.e., knowledge and skills, and dispositions to use data)". The implementation of data-driven decision making with the support of data analytics tools in HEIs faces various technological obstacles, including those related to privacy, as well as the ethical and conscientious utilisation of data (Webber & Zheng, 2019a). The effective establishment of a culture centred on data-driven decision-making within HEIs necessitates the presence of skilled personnel, technologies facilitating data integration, systems for data management, as well as tools for reporting, analysis, and data visualisation (Webber & Zheng, 2019b).

Overall, Webber and Zheng (2019a) suggest that in order to effectively utilise data analytics for DDDM, it is crucial to focus on developing the necessary components of people, processes, technology, and culture. Otherwise, insufficient or ineffective development of the above four technology development components negatively influence the implementation of DDDM in HEIs.

In Ethiopia, the government has prioritised the advancement of information and communication technology (ICT) and has made a significant investment in this area (Alemu, 2017). Furthermore, there is a programme promoting digital innovation in Ethiopia (MinT, 2022). Nevertheless, the Ethiopian higher education system is facing continuous quality challenges (Tareke et al., 2024). Moreover, the ICT infrastructure that is expected to support the process of improving education quality is underutilised (Ergado, 2019; Yallew, 2020; Alemu, 2017 Waweru and Abate, 2013; Ferede et al., 2022). Studies indicate that faculty members in Ethiopian universities analyse student-related data manually than using the latest data analytics technologies (Akal et al., 2019). This shows that the significant volume of data produced on a daily basis in Ethiopian higher education institutions is not effectively utilised with modern data technologies to enhance the quality of education. The research conducted by Assefa (2019) revealed that software products are underutilised in Ethiopian universities, with many departments lacking the necessary software support to carry out tasks and offer standardised services. With the high rate of enrolment (Yallew, 2020), shortage of skilled academic staff, high work load on educators, insufficient support of students, and the presence of millions of invested underutilised ICT resources, it is reasonable to adopt DDDM in HEIs in Ethiopia to resolve some of the educational problems.

Research shows that schools that consistently and effectively utilise data have observed a significant improvement in student performance (Terrill, 2018). According to Denny (2020), data is utilized in decision-making processes such as aligning instruction with standards, setting objectives, monitoring progress, identifying underperforming students, and planning instruction. Additionally, Hughes (2016) cited in Denny (2020) highlighted the significance of data in shaping policies and educational resources. The systematic gathering and utilisation of data can help education leaders identify service gaps, address inequalities, and assess the effects of various interventions on learning outcomes (UNESCO IIEP, 2020). Given the broad impact of data-driven decision-making in education, it is crucial that it is carried out accurately and consistently (Denny, 2020). The current study by Gaftandzhieva et al., (2023) emphasised the importance of using DDDM tools to improve academic performance and support sustainable development. Furthermore, the utilisation of decision-making systems in higher education helps to minimise the resources required to identify issues, challenges, or barriers within higher education systems and arrive at optimal decisions (Fakeeh, 2015; Acevedo et al., 2018).

This study's focus is on DDDM to improve higher education quality. Specifically, the type of decision expected pertains to teaching and learning activities. The scope of decisions extends from individual students to faculty level. This means that decisions will be about individual student success and failure, decisions about the classroom, decisions about the

department, and decisions about faculty will be done in terms of student success and failure. Thus, with the help of intelligent data analytics systems, respective stakeholders take necessary measurements to address risks about students, classrooms, departments, and faculty before it happens. This helps to provide effective support for those who need it. In addition, DDDM helps in forecasting student, departmental, and faculty success and failure. In this process, the progress of students and faculty staff will be evaluated, and resources will be allocated to increase educational quality. This proactive approach not only enhances the learning environment but also fosters a culture of continuous improvement within the institution. By leveraging data-driven insights, educational leaders can make informed decisions that ultimately lead to better educational outcomes for all stakeholders involved.

In this context, an authorised person will collect and use information on students' background, family, student achievement, attendance, demographics, behaviour, student feedback, student attitude, motivations, and additional information needed to support student accomplishment in order to make decisions. Similarly, data on instructors, department heads, department coordinators, faculty deans, and other supportive work process will be collected and analysed in order to increase student achievement.

According to Shacklock (2016), HEIs collect both static and fluid data. Static data is data that institutions gather, record, and store, and it typically includes student records, staff data, financial data, alumni data, admissions and application data, course data, facility data, and other additional data. Fluid data is generated by the increasingly digital method by which students interact with their university, such as swipe card data from access-controlled campus buildings, log-ins to the virtual learning environment (VLE), and E-books and online journal downloads. More specifically, website usage, emails, and social network usage data are collected to make decisions in HEIs. Static data has long been a valuable resource for institutions and governments, guiding operational and business decisions as well as providing insights into sector performance for both the government and the public, a situation that applies to Ethiopia as well. Fluid data, when effectively collected, linked, and analysed, can offer a real-time and precise assessment of a student's performance. In Ethiopia, higher education institutions gather static data as discussed above. However, data on student behaviour, attitudes, and feedback are not systematically collected, stored, or utilised to enhance student success. Most data related to registration and assessments are managed by the registrar, with limited access for instructors and students. Many higher education institutions in Ethiopia rely on various in-house developed and customised open-source software and disconnected systems, yet their decision-making processes lack support from advanced data analytics systems. As noted in this study, faculty members at Ethiopian universities often analyse student data manually rather than employing modern data analytics technologies. For instance, the registrar uses static assessment data to determine whether students pass or fail to advance to the next academic level or graduate. In contrast, one participating university in our research utilised data analytics software in its library system to evaluate research publication output and provide insights for academic rank promotion decisions; however, this software was outdated and non-functional during our data collection. According to Akal et al. (2019), higher education staff frequently engage in the manual analysis of student performance data or utilize Microsoft Excel as a tool for decision-making purposes. True DDDM, however, goes beyond this; it involves integrating and analysing both static and fluid data to gain a comprehensive understanding of student performance, ultimately leading to improved outcomes for both students and institutions. Furthermore, educators around the globe commonly use student data as a crucial tool to enhance student learning and academic achievement (Kaspi & Venkatraman, 2023). Thus, in this context, DDDM is necessary for improving the standard of education in Ethiopian higher education.

While a wealth of research exists regarding barriers and facilitators in implementing DDDM in higher education in the developed countries, there remains a lack of comprehensive studies regarding barriers and facilitators for the implementation of DDDM in HEIs in resource constrained developing countries, including Ethiopia.

The adoption of DDDM in higher learning institutions in Ethiopia in the future may encounter various obstacles. Therefore, this research seeks to identify the potential barriers and facilitators of implementing DDDM methods in higher learning institutions in Ethiopia in the future. Gaining insight into potential barriers and facilitators will speed up the execution of data-driven decision-making (DDDM) in Ethiopia and provide guidance for its implementation in similar contexts in other developing countries. Consequently, this is anticipated to result in enhanced educational quality.

Methods

Study Design

This research employs the modified Delphi method to determine the barriers and facilitators for implementing data-driven decision making (DDDM) in higher education institutions (HEIs) in Ethiopia, as perceived by experts in Ethiopian HEIs. The Delphi method is frequently employed to combine the knowledge of experts in situations where existing information

is lacking or uncertain, and when other methods with stronger evidence cannot be applied (Niederberger & Spranger, 2020). In this study, the Delphi method was chosen because barriers and facilitators for implementing DDDM in Ethiopian HEIs cannot be easily investigated using conventional survey or experimental methods, as educational practices vary based on demographics, policies, and the nature of institutions in different contexts. Subjective expert judgment is necessary due to the complexity of DDDM. A modified Delphi method is appropriate because it allows researchers to tailor the process to specific research questions by adjusting the initial set of items or questions presented to the expert panel, leveraging existing knowledge from literature reviews or stakeholder input, while still maintaining the core principles of anonymity, iteration, and consensus building inherent in the Delphi technique. In a modified Delphi technique, a team of researchers selects crucial concepts from existing literature, which are then presented to a group of specialists for prioritisation (Oxley et al., 2024). Alternatively, the initial phase of the Delphi process may involve posing open-ended inquiries (Keil et al., 2002), enabling participants to highlight concepts of particular significance to them. The adaptation in this investigation entailed commencing with a meticulously curated initial compilation of obstacles and enablers sourced from literature that influence the implementation of DDDM in Ethiopian higher education. This was to lessen the workload on the expert panel. In addition, the panellists were given the power to identify additional barriers and facilitators.

Study Participants and Data Source

In order to collect data, we sought the assistance of two prominent first-generation universities with high student population and faculty demographics and better information and communication technology infrastructure in comparison to more recently established universities (Ferede et al., 2022). The university leaders identified 57 individuals with expertise in data-driven decision-making and educational technologies. The inclusion criteria required individuals to possess knowledge about DDDM, data systems, and educational technologies, as well as a minimum of 2 years of work experience. ICT specialists were expected to have knowledge of educational technologies and a deep understanding of data infrastructure. Recruitment took place on February 6, 2023.

A total of 63 participants were invited to join the Delphi expert panel, with 57 agreeing to participate. The 57 participants comprised nine ICT specialists, two directors from the Office of Education Program Relevance and Quality Enhancement, and 46 higher education instructors. The ICT specialists included team leaders, such as the Infrastructure and Service Team Leader, Teaching Learning Technologies Team Leader, Technical and

User Support Team Leader, Training and Consultancy Team Leader, and Application Development and Execution Team Leaders. The instructors included faculty deans, department heads, department coordinators, and instructors from the departments of information science, computer science, information technology, software engineering, and computer networking.

Table 1: Participants characteristics

No.	Departments	Gender		Academic Qualification			Work experience
		Male	Female	Bachelor Degree	Master's Degree	PhD	Above two years, and most of them have more than 12 years of experience.
1	Faculty members	38	8	-	35	11	
2	ICT specialists	9	-	1	7	1	
2	Education programme relevance and quality assurance	2	-	-	-	2	

This research was carried out over a period of six months, from February to July 2023, utilising the modified Delphi method across three iterative rounds. A web-based questionnaire was employed for the survey, with the exception of the second round, which utilised the Microsoft Word checkbox feature and was distributed via email. The survey instruments were developed using Google Forms, and invitations were subsequently dispatched to participants via email. Prior to conducting the survey, the instruments underwent pilot testing by six voluntary experts. The experts who participated in the pilot test were three PhD holder faculty members, two M.Sc.-holder ICT experts, and one PhD holder education programme relevance and quality enhancement officer. All six experts engaged in the pilot test have experience in educational technologies. Feedback on the clarity and ease of completing the survey was obtained and used to modify the questions accordingly. Prior to sending out the invitations, a member of the research team, Zelalem Asfaw, engaged in telephone communication with each participant. Throughout each round, invitations to the survey were extended to panel experts who had previously agreed to take part, irrespective of their involvement in the preceding round. As an adjustment of the Delphi method, a thorough examination and analysis of existing literature was undertaken to create a compilation of obstacles and enablers for the adoption of DDDM. This involved the meticulous design of key terms (i.e., data-driven decision-making, data analytics, data use, data-driven approach, educational technology, and higher education) and

a scoping review of databases to identify relevant literature. Prior to the actual literature search, the key terms were tested across multiple databases. Subsequently, the researcher (Zelalem Asfaw) identified the barriers and facilitators following a thorough comprehension of the literature. The extracted lists of barriers and facilitators were deliberated among the researchers, leading to the development of an initial list of barriers and facilitators.

In the initial phase, the panel was tasked with selecting the significant barriers and facilitators from a predetermined list of 20 barriers and 16 facilitators, and also identifying any additional barriers and facilitators through open-ended questions. After removing duplicates, the participants specified 19 barriers and 4 facilitators. The specific questions for each round are presented in Table 2.

Subsequently, in the second phase, the panel was required to assess a total of 39 predefined and added barriers, as well as 20 facilitators, employing a 5-point Likert scale. For barriers: 5 (extremely obstacle), 4 (fairly obstacle), 3 (obstacle), 2 (slightly obstacle), and
1 (not at all obstacle). The index numbers were utilised to show the ratings of the items based on how important they were perceived to be.

Table 2: Objectives and Questions in Every Cycle

Purpose	Specific Questions	Question Types
Round 1		
Choosing obstacles and enablers from the preliminary compilations.	What barriers prevent you from implementing data-driven decision-making in teaching and learning activities at your university? Please check if that applies to you.	Selecting questions (Check-box)
	What enablers could help support the adoption of data-driven decision-making in teaching and learning practices at your university? Please check if that applies to you.	Selecting Questions (Check-box)
	What, if any, barriers do you experience in implementing data-driven decision-making to improve the quality of education at your university?	Open ended

	What, if any, facilitators do you consider in implementing data-driven decision-making in order to improve education quality at your university?	Open ended
Round 2		
Assessment of obstacles chosen in the first round	Please evaluate the potential obstacles based on their importance to implementing DDDM in HEIs in Ethiopia.	5-point Likert scale: Not at all Obstacle Slightly Obstacle Obstacle Fairly Obstacle Extremely Obstacle
Evaluation of facilitators selected in round 1	Please evaluate the potential enablers based on their importance to implementing DDDM in HEIs in Ethiopia.	5-point Likert scale: Strongly Disagree Disagree Neither Agree nor Disagree Agree Strongly Agree
Round 3		
Priotrisation of barriers and facilitators selected in the second round	In this phase, we kindly request that you prioritise the following barriers: Please assign a number from 1 to 10, with 10 indicating the lowest priority.	
	In this phase, we kindly request that you prioritise the following facilitators: Please assign a number from 1 to 4, with 4 indicating the lowest priority.	Ranking

In the concluding stage, individuals were tasked with prioritising the primary obstacles and enablers that must be tackled to effectively introduce a data-driven decision-making approach within higher education establishments in Ethiopia moving forward. The participants were asked to assign a score of 1 for the highest priority and 10 for the lowest priority for barriers and facilitators. In a way, they were requested to prioritise the

items from most significant to least significant. The ten most frequently cited barriers and facilitators are shown in Tables 3 and 4.

Table 3: The top ten Barriers to Implementing DDDM in Ethiopian HEIs, Ranked by Their Level of Significance

No.	Barriers	Round 2 (n=51)		Round 3 (n=48)	
		%	n	Mean Rank	Rank
1	Lack of DDDM policy	84	43	4.50	1
2	Organisational culture	82	42	4.39	2
3	Lack of DDDM culture	80	41	4.33	3
4	Lack of clear ICT policy	76	39	4.31	4
5	Lack of awareness and commitment of management bodies	76	39	4.29	5
6	Lack of budget/ associated cost	76	39	4.26	6
7	Lack of data management policy	78	39	4.11	7
8	Accessibility of data	76	39	4.09	8
9	Lack of collaboration between different stakeholders	80	39	4.02	9
10	Lack of sustainable investment on DDDM	82	39	4.00	10

'n' is the number of panel experts

The result of the findings in Table 3 indicates the lack of DDDM policy is the most significant factor (84% of experts agreed on) that might inhibit the adoption of DDDM in higher learning institutions in Ethiopia. It indicates its important since strategies and plans originate from policy. The (82% of experts) also indicated organisational culture is the next influential barrier that inhibits the implementation of DDDM. It is well understood that any practice is executed within the context of an organization. Consequently, the inherent attributes of the organization—such as its norms, vision, collaborative efforts, and leadership—significantly impact the implementation of DDDM in HEIs in Ethiopia. As indicated in the Table, out of ten high barriers three of them are policy issues, whereas lack of sustainable investment on DDDM is identified as the least important factor. This in turn implies the practice of DDDM is not a one-time job but needs continuous investment and support. The result from the panel of experts indicates that except barriers related to accessibility of data, all the identified barriers are in the category of organisational characteristics. In a broad sense, the identified barriers indicate the need for managerial perspectives rather than purely technical viewpoints.

As indicated in Table 4, a group of experts also identified and prioritized facilitators for the successful implementation of DDDM. The panel of experts (96%) agreed on the presence of network infrastructure as the most important facilitator in Ethiopian HEIs. The availability of good bandwidth internet was agreed upon by 92% of the expert panels, followed by the availability of skilled ICT specialists, which was also identified as a third level facilitator. The availability of computer access to students at the university level was also agreed upon as the last facilitator. However, among the 20 facilitators identified in the literature and added by the expert panellist group, only four of them reached consensus on facilitators in HEIs in Ethiopia. This indicates that rather than focusing on facilitators, it is imperative to look at barriers to the successful implementation of DDDM in Ethiopia.

Table 4: Top four facilitators for implementation of DDDM in HLIs

No.	Facilitators	Round 2		Round 3 (n=48)	
		%	n	Mean Rank	Rank
1	Presence of network infrastructure	96	46	4.30	1
2	Availability of good bandwidth internet	92	44	4.24	2
3	Presence of skilled ICT specialists	90	43	4.06	3
4	Availability of computer access to students at the universities	85	41	4.00	4

In addition to barriers and facilitators identified through an extensive literature review conducted by the researchers, further barriers and facilitators were gathered from the initial round of expert input. The researcher (Zelalem Asfaw) then evaluated the resemblances and disparities of the barriers and facilitators identified by the first-round panel of experts and those pre-identified from the literature review. These discoveries were subsequently deliberated with the research team. Furthermore, all of our questionnaires for each round contained an open comment section, allowing the panel of experts to freely express their opinions. Throughout each round, the researchers sent three reminders (i.e., weekly) to all participants to complete the questionnaire by scheduled date.

In this investigation, consensus was defined as the point at which the combined proportion of ratings 4 and 5 reached 80% or more for enablers, and the combined proportion of ratings 3, 4, and 5 reached 80% or more for barriers. It is worth noting that the Delphi method conventionally employs a threshold of 70% or more for consensus (Vernon, 2009). The mean scores were computed to assess the significance of barriers and facilitators.

Limitations of the Study

The initial compilation of barriers and facilitators was formulated by a sole researcher and subsequently deliberated with members of the research team. This approach may introduce partiality. Nevertheless, the utilisation of the Delphi method affords the opportunity to eliminate and introduce new elements, thereby mitigating potential bias. Furthermore, the participants were drawn from two well-established universities in Ethiopia. It is imperative that we acknowledge that this sample may not be fully representative of all universities in Ethiopia. Nonetheless, endeavours were made to encompass a diverse array of potential stakeholders, which may bring to light context-specific concerns.

Results

Summary of Responses

In the initial round, 54 out of 57 respondents participated, resulting in a response rate of 94.73%. The second-round garnered participation from 51 out of 57 respondents, yielding an 89.47% response rate, whereas in the concluding phase, 48 out of 57 respondents took part, resulting in an 84.21% response rate.

Summary of the Three Rounds

In the initial round, the panel was presented with 20 obstacles and 16 enablers that helped facilitate the discussion, and experts also identified 19 additional barriers and 4 additional facilitators. In general, 39 barriers and 20 facilitators were identified as potential factors in the first round (see Tables 5 and 6). In the subsequent phase, a total of 39 obstacles and 20 enablers were identified, and consensus was reached on 21 barriers and 4 facilitators (see Table 7). In the concluding phase, the panel was requested to provide rankings of the 10 most important barriers and facilitators that need to be addressed for the implementation of DDDM in Ethiopian HEIs.

Table 5: All Identified Barriers in the First Round

No.	Barriers Identified from Literature	No.	Barriers Identified by Panel of Experts
1	Lack of DDDM policy	21	Lack of autonomous authority
2	Organisational culture	22	Lack of culture of recording data
3	Lack of DDDM culture	23	Lack of effective standards
4	Privacy and security issues	24	Political issues
5	Lack of awareness and commitment of management bodies	25	Lack of effective tools
6	Lack of budget/ associated cost	26	Lack of clear ICT policy

7	Lack of data management policy	27	Quality of data
8	Accessibility of data	28	Lack of good bandwidth of internet
9	Lack of collaboration between different stakeholders	29	Timeliness of data
10	Lack of sustainable investment on DDDM	30	Challenge of integrating different databases from different sources
11	Data literacy in education	31	Institutional resistance (change resistance)
12	Stability of government policy	32	Lack of motivation to use data
13	Lack of linkage to external data intensive technology	33	Lack of availability of data
14	Lack of leadership support	34	Extra work load
15	Lack of training on data usage/DDDM	35	Lack of time for implementing DDDM
16	Lack of data infrastructure	36	Complexity of organizational structure
17	Lack of Network infrastructure	37	Lack of government incentives
18	Staff Capacity and support	38	Knowledge of students
19	Curriculum pacing pressure	39	Ministers of Education and Finance: Regulation related obstacles
20	Lack of data analyst and scientist/Lack of expertise staff/		

Table 6: All identified Facilitators in the First Round

No.	Facilitators Identified from Literature	No.	Facilitators Identified from Literature
1	Availability of policy regarding implementing data-driven decision-making	11	Good culture of data-driven decision-making
2	Availability of data management policy	12	Accessibility of data
3	Sustainable investment on data-driven decision-making	13	Timeliness of data
4	Presence of leadership support	14	Availability of adequate time to practice data-driven decision-making
5	Availability of training	15	Presence of institutional researcher
6	Presence of robust data infrastructure	16	Presence of data analyst and/ or scientist
			Facilitators Identified by Panel of Experts
7	Presence of Network infrastructure	17	Presence of skilled Information Technology experts
8	Availability of good bandwidth internet	18	Flexible organisational structure
9	Presence of linkage to data intensive industry	19	Availability of computer access to students at universities
10	Presence of privacy and security management systems	20	University Autonomy /Self-governance

Table 7: Consensus Reached 21 Barriers and Four Facilitators in the Second Round

No.	Barriers	No.	Barriers
1	Lack of DDDM policy	12	Lack of training on data usage/ DDDM
2	Organizational culture	13	Lack of leadership support
3	Lack of DDDM culture	14	Lack of effective standards
4	Lack of clear ICT policy	15	Lack of government incentives
5	Instability of government policy	16	Lack of linkage to external data intensive technology organisations
6	Lack of budget/ associated cost	17	Accessibility of data
7	Lack of data management policy	18	Timeliness/ up-to-date data
8	Lack of data analytics tools	19	Challenge of data integration from different data sources
9	Lack of collaboration between different stakeholders	20	Data literacy in education
10	Lack of sustainable investment on DDDM	21	Lack of culture of data recording
11	Lack of awareness and commitment of management bodies		
No.	**Facilitators**		
1	Presence of network infrastructure		
2	availability of good bandwidth internet		
3	presence of skilled ICT specialists		
4	availability of computer access to students at the universities		

Barriers

Among the 21 barriers identified in Table 7, the 10 barriers deemed to be of most importance for resolution include: absence of a DDDM policy (rated at 4.50 points), organisational culture (4.39), lack of DDDM culture (4.33), absence of a clear ICT policy (4.31), lack of awareness and commitment from management bodies (4.29), insufficient budget and associated costs

(4.26), absence of a data management policy (4.11), data accessibility (4.09), lack of collaboration among various stakeholders (4.02), and inadequate sustainable investment in DDDM (4.00). These barriers may have adverse effects on the successful implementation of DDDM in Ethiopian universities.

Facilitators

The four facilitators listed in Table 7 were determined to be of high importance for the implementation of DDDM. These facilitators include the presence of network infrastructure (4.30), the availability of good bandwidth internet (4.24), the presence of skilled ICT specialists (4.06), and the availability of computer access to students at the universities (4.00). In the truly data-driven decision-making system, data from all stakeholders is collected and analysed to make decisions. Thus, the availability of computer access to students at the university level enables students to communicate with the respective stakeholder, which aids in decision-making. In general, the above factors might facilitate the execution of data-driven decision-making in universities in Ethiopia.

Discussions

This research investigated the factors that hinder or support the adoption of data-driven decision making (DDDM) in universities in Ethiopia. The study utilised a modified Delphi method to establish expert consensus. The findings highlighted the significance of several barriers, including the absence of a DDDM policy, organisational culture, and ICT policy, as well as lack of awareness and commitment from management bodies, budget constraints, and lack of data management policies. Additionally, limited collaboration among stakeholders and insufficient sustainable investment in DDDM were identified as impediments. Conversely, the presence of network infrastructure at universities was recognised as a facilitator. The study also emphasised the importance of good-bandwidth internet, computer access for students, and skilled information technology experts as essential facilitators for the successful execution of DDDM in universities in Ethiopia.

Barriers

The study identified critical barriers, such as a lack of data-driven decision-making policy, a lack of data management policy, and a lack of ICT policy. Policy is the main driver as it provides principles and plans as a foundation for action, decision-making, and problem-solving initiatives aimed at facilitating the adoption of data-driven decision-making practices within Ethiopian HEIs. Policy plays a crucial role in setting a clear vision and goals that are necessary for effective utilisation of data, as emphasised by Wohlstetter et al. (2008) and Wayman et al. (2007). These are the most important barriers that should be addressed before the implementation of DDDM in HEIs in Ethiopia.

Previous studies in other countries have indicated that to execute DDDM in the educational sector, it is important to address critical issues related to policies. To effectively incorporate and achieve the goal of improving education quality through the utilisation of DDDM in higher learning institutions, it is crucial to establish policies that support data collection, access, utilisation, and data analytics. The research conducted by Webber and Zheng (2019) centred on the advancement of data-informed decision-making and analytics maturity within the realm of higher education states the importance of policy. It highlighted policies as a critical element among the six key components essential for enhancing analytics maturity in the context of implementing data-informed decision-making in higher education. In a similar way, the study by Dahlstrom (2016) focused on identifying data analytics maturity models for implementing DDDM in higher education, identified policies related to data collection, management, access, and sharing as crucial dimensions. In a similar fashion, Gill et al. (2014), in their study with the objective of developing a conceptual framework for DDDM in education, indicate that the implementation of DDDM is contingent upon the presence of supportive infrastructure, policies, and practices. Thus, our findings regarding the significance of policies for the execution of DDDM in higher education complement those of Webber and Zheng (2019), Dahlstrom (2016), and Gill et al. (2014). Research indicates that not only the availability of data-related policies but also specific policies implemented by different countries can impact the availability and accessibility of data for educational institutions. These policies have the dual effect of influencing and assisting educational institutions in their utilization of data (Schildkamp et al., 2013).

The results of this study also suggest that organisational culture within Ethiopian higher education institutions (HEIs) has an impact on the execution of DDDM. Moreover, the lack of DDDM culture, lack of awareness and commitment from management bodies, and insufficient collaboration among stakeholders were identified as factors that negatively affect the effective implementation of DDDM in HEIs in Ethiopia. The study by Schildkamp et al. (2016), which focuses on conditions for data use, identified that organisational characteristics influence data usage in educational institutions, which also aligns with our findings. To foster a culture of DDDM in the education system, it is crucial to have dedicated leadership and accountability systems in place. The study by Tabesh et al. (2019), focusing on the managerial perspectives of big data implementation, indicates that the attitudes of top managers towards DDDM can significantly influence decision-making patterns throughout the organisation. Furthermore, Rasmussen and Ulrich (2015) found that important organisational decision-makers have a significant impact on the achievement or failure of data use initiatives. This underscores the importance of leaders in establishing a vision, norms, and goals for data utilisation within an organisation. The findings of Tabesh et al. (2019) suggested that managerial commitment and support can effectively address cultural and technological barriers to data use, which complements our findings. Data use is inherently a collaborative activity, and collaboration around data usage has been emphasised in various studies (Datnow & Park, 2013; Schildkamp et al., 2016). The utilisation of data to inform decision-making is a collaborative endeavour, and therefore, the establishment of an analytics programme aimed at enhancing decision-making across an organisation requires a collaborative approach both internally and externally (Dahlstrom, 2016; Webber & Zheng, 2019). Our finding regarding collaboration in DDDM also complements the previous studies.

The research findings also suggested that the absence of adequate funding and sustainable investment could have a detrimental impact on the integration of DDDM in higher educations in Ethiopia. Given that DDDM is a sophisticated technology, it necessitates investment in professional development, tools, and technologies that enable educational institutions to fulfil their objectives of enhancing the quality of education. Prior research has highlighted the necessity of transitioning towards a data-driven education system and has recommended investing in human resources, technology, and tools (Webber & Zheng, 2019). As Chui (2016) has observed, cost has been a significant barrier to the adoption of intelligent decision-making in educational institutions.

Furthermore, our study has identified that the lack of accessibility of data hinders the adoption of DDDM in Ethiopian HEIs. Previous studies have also emphasised the importance of ensuring that faculty members and other stakeholders have access to necessary data for decision-making, as the lack of access could pose a significant obstacle to data utilisation (Schildkamp et al., 2013; Marsh et al., 2006). In a broad sense, except for issues related to data accessibility that might happen due to technological or managerial limitations, our panel of experts agreed more than 90% of barriers (such as policy issues, leadership, organisational culture and cost related issues) for the implementation of DDDM in HEIs in Ethiopia may face obstacles related to organisational or managerial perspectives. In agreement with Tabesh et al. (2019), as well as Rasmussen and Ulrich (2015), the study

results indicate that the success or failure of data use depends organisational or managerial commitments to technological requirements.

Facilitators

Among the four facilitators identified in Ethiopian HEIs for the implementation of DDDM systems, except for the availability of skilled ICT specialists, three of them are subgroups of infrastructure. Specifically, the presence of network infrastructure, the availability of high-bandwidth internet, and access to computers for students at universities. This indicates that Ethiopian higher education institutions (HEIs) have a foundation in network infrastructure for implementing DDDM. A study by Schildkamp et al. (2013) focusing on DDDM indicates the importance of data and data systems for the adoption of DDDM in educational institutions. In a similar way, the study by Bolhuis et al. (2016) focused on identifying obstacles and facilitators for DDDM in teams, which indicates the necessity of data and data systems. Furthermore, the study by Chui (2016) focused on transforming educational institution management and decision making through DDDM, which indicates the necessity of data and data systems for the implementation of DDDM. Thus, our result regarding the availability of data (the network) complements the previous studies. In line with the availability of data systems, the HEIs have been using some educational software products for their daily teaching and learning activities, including student information systems for registration and grading and other research management applications. This will help in the fast implementation of DDDM in HEIs in Ethiopia.

However, the study by New (2016) focusing on creating a data-driven education system in the USA indicated that a data-driven education system would rely on various educational technologies specifically designed to improve every facet of the educational process. These technologies include the student information system, the learning management system, and the data warehouse. Through the lens of New (2016), our findings indicate the Ethiopian HEIs have in house-designed student registration systems for registration and grading purposes. In addition, the findings indicate that there was a practice of using LMS like Moodle during COVID-19 but it is not in use now. The data warehouse is unavailable. In general, the Ethiopian HEIs have limited facilitators for the implementation of DDDM.

The study by Webber and Zheng (2019) indicates that to successfully implement DDDM in higher education, it needs four essential components: technology, people, process, and culture. However, our findings indicate that there are limited facilitators for the execution of DDDM in higher education institutions in Ethiopia, calling for forward thinking and workable solutions.

Conclusions and Recommendations

The objective of this investigation was to determine the barriers that hinder and enablers that facilitate the execution of DDDM in universities in Ethiopia. We have identified 10 key barriers and four facilitators. The top three barriers are lack of DDDM policy, organisational culture, and lack of DDDM culture. The availability of network infrastructure, access to good bandwidth internet, and the presence of skilled ICT specialists were identified as the top three facilitators. The results of the study indicate Ethiopian HEIs may encounter organisational or managerial barriers more than technological ones. Despite the unique contexts of universities in developing countries, the result of this study might be extended to other HEIs in other developing countries. In this study, policy appears to be the key and essential factor for the implementation of DDDM in HEIs in Ethiopia and in developing countries.

This research illustrated the significance of implementing a policy that serves as the cornerstone for fostering a culture of DDDM within HEIs in Ethiopia. The policy is designed to facilitate the collection, access, sharing, scrutiny, and interpretation of data to enhance the quality of education. Additionally, the policy is instrumental in promoting the commitment and accountability of managers and stakeholders, as well as in facilitating the efficient allocation of budget and resource management. Moreover, the policy plays a crucial role in establishing structured collaboration between internal and external stakeholders to ensure the effective implementation and execution of DDDM in HEIs in Ethiopia. Further insight gained from this research is that higher education institutions, such as Ethiopia, need to resolve or give equal opportunity to organisational barriers as well as technological barriers in order to successfully implement DDDM.

Future research should be conducted on identifying strategies for eliminating barriers and advancing facilitators in HEIs for the implementation of DDDM to improve the quality of education.

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