School Leaders' Perceptions of Their Schools' Readiness for Data-Driven Leadership in Al Dhafra Region Cycle 2 and 3 Public Schools'

Mahmoud Hamash[1*], Hanan Ghreir[2], Hasnah Mohamed[1]
[1]Universiti Teknologi Malaysia, Malaysia
[2]University Sains Malysia, Malaysia
*mohammad20@graduate.utm.my, hanan-ghreir127@student.usm.my, hasnah-m@utm.my

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ABSTRACT

There is a growing need for Data-Driven Leadership (DDL) in the UAE, and while the implementation frameworks serve as a grounding approach for implementing DDL, there has yet to be an application of this concept in the UAE school context. This research aims to assess the readiness of Al Dhafra cycle two and three public schools for DDL implementation. The study used the survey research quantitative method design based on the Active Implementation Framework (AIF) drivers. The researcher surveyed sixteen school principals from nineteen cycle two and three public schools in Al Dhafra region, using the School Principal questionnaire. The sampling method used was simple random sampling. Descriptive analysis was used to analyse the collected data. The research findings suggest that principals are more ready for DDL in terms of organisational drivers than competency drivers. However, their readiness for DDL at the leadership level is less clear, with items for that driver falling between the highest and middle-scoring groups. School principals identified competency, organizational, and technical leadership drivers as key implementation drivers for improving DDL in their schools. The research recommends further study to understand the role of adaptive leadership in successful DDL implementation. In conclusion, this research has provided valuable insights into the implementation of DDL in Al Dhafra cycle two and three public schools and highlighted the importance of various AIF drivers to the successful implementation of DDL.

Keywords
Data-driven leadership; Educational leadership; Educational technology, Active Implementation Framework (AIF); Implementation Science.

Introduction

The main three factors that have significantly impacted education through leadership in recent years are the increasing use of technology in the classroom, the need for school leaders to be data-driven, and the growing emphasis on school accountability (Fowler & Brown, 2018). Consequently, reforms in education were necessary to achieve the desired results required to face these issues. A key reform trend is Data-Driven Leadership (DDL). DDL recognizes the importance of utilizing data to improve schools and student achievement, connect and drive accountability, and measure school security and student achievement. A school system's ability to acquire, analyze, share, and act upon data is crucial to the success of every student (Jones & Kennedy, 2015). Accordingly, educational leaders have begun using data to guide and inform school improvement efforts, creating a worldwide demand for insights and data. School leaders in the United Arab Emirates have long been collecting and using data to inform their Data-Driven Decision Making (DDDM) and Data-Driven Instruction (DDI), through evaluating student performance, tracking assignments, and scores on standardized testing. This was apparent to the researcher as he interacted with Al Dhafra region school leaders in his profile as a leader in implementing digital learning and educational technologies, which has a massive component of data-use, DDDM, DDL, and DDI. The researcher believes DDL is essential to improving education in the United Arab Emirates. Thus, gaining a deeper understanding of how school leaders rate the current school readiness level for DDL in UAE public schools will positively affect the education system and support the efforts of implementing DDL.

According to Uding (2022), Data-Driven Leadership (DDL) integrates leadership, change-management, and data analytics in a progressive work environment. Essentially, DDL is an organizational competency that improves communication between processes, evaluations, outcomes, and learning. School leaders can gain a comprehensive view of student progress, challenges, and performance. This visibility allows teachers and leaders to make well-informed decisions regarding interventions that can enhance student learning. An article published by Aryng (2011) highlights the importance of DDL in building data literacy within an organization. As per Aryng, it is nearly impossible to improve an organization's data literacy without a leader who understands data and uses it in decision-making processes. This research defines DDL as a leadership model that focuses on creating a data-driven school culture, utilizing metrics such as learning, behavior, and engagement to uncover patterns in student learning, promote professional growth, instructional improvement, and empower student success.

The implementation drivers for DDL within schools, as discussed in the literature, are crucial in guiding efforts to implement DDL (Barton, 2019). Despite the recognition by school leaders, educational authorities, and researchers of the need to support school principals in analyzing and utilizing data, there is a lack of theoretically sound research on DDDM and DDL (Marsh & Farrell, 2014). Undoubtedly, the push for data-driven initiatives has led to the incorporation of DDL practices. However, educational organizations do not always fully integrate DDL (Coulton, Clift, Skingley, & Rodriguez, 2015). Building on the existing literature, this research seeks to understand how school leaders rate their schools' readiness for Data-Driven Leadership in Al Dhafra Region Cycle 2 and 3 Public Schools.

Literature Review

Abu Dhabi has recently undergone significant educational changes, including the implementation of data-driven educational leadership. According to Madden (2019), the call for external accountability has motivated school leaders to establish data-driven practices and incorporate them into school-wide procedures, ultimately impacting teaching and learning. The researcher also notes that while many studies have focused on the importance and effects of DDL, others have investigated the requirements and capacities necessary for successful implementation. Research by Litz, Smith, & Hourani (2019) suggests that schools in Abu Dhabi must expand their capacity and upgrade their operations to meet the evolving needs of dynamic learning and DDL. Additionally, Alzuhair (2018) asserts that there is a lack of research on DDL practices in UAE schools, and more literature is needed to gain a deeper understanding. It is essential to recognize that there are various aspects involved in developing school DDL, making it crucial to measure school readiness before implementing these practices. Despite the growing interest in implementation science over the last twenty years (Barton, 2019), a scoping review of 8541 publications from various databases by Albers, Mildon, Lyon, & Shlonsky (2017) showed limited evidence of its application in educational programs. Another study by Alzuhair (2018) utilized a qualitative method, specifically the grounded theory approach, through interviews with school leaders to gather information on DDL practices in UAE schools.

As explained by Malecki (2021), the field of implementation science focuses on systematically translating and integrating research-backed innovations and evidence into standard procedures. In the last two decades, numerous frameworks have been developed to guide and improve research in this area (Moullin, sabater-hernández, Fernandez-Llimos, & Benrimoj, 2015; Nilsen, 2015; Tabak, Khoong, Chambers, & Brownson, 2012). One example is the Active Implementation Frameworks (AIF), developed by the National Implementation Research Network (Metz et al., 2014), which focuses specifically on factors influencing the adoption of evidence-based approaches. The use of implementation frameworks has become increasingly significant in understanding the successful implementation of DDL in education, as revealed by a scoping review by Albers, Mildon, Lyon, & Shlonsky (2017) which identified eight implementation frameworks used in thirty-three studies. Of these, the AIF-drivers were the most used. Among these studies, nine focused on evaluating the application of AIF-Drivers in educational programs. (Nilsen, 2015) further emphasized the importance of choosing the right implementation framework to achieve effective results, suggesting the AIF as a rational approach. AIF-Drivers fall into three categories: competency drivers (Fixsen et al., 2015), organizational drivers (Metz & Bartley, 2012; Metz et al., 2014), and leadership drivers (Metz et al., 2014). Building on the AIF-Drivers, Barton (2019) developed and initially validated a new tool to measure program readiness for DDL, following recommendations by Goodwin (2002). His findings demonstrate the viability of using the nine AIF-Drivers to measure data use and DDL readiness. This literature review has provided the researcher with a comprehensive understanding of how to measure school readiness for implementing Data-Driven Leadership in Al Dhafra region public schools.

Methods

This research project used the survey research quantitative method design based on the Active Implementation Framework (AIF) drivers. The specific choice of this design was due to limited literature regarding data-driven educational leadership in the UAE. The researcher conducted the quantitative data collection using simple random sampling. This is where a subgroup is drawn from a population, and all individuals have an equal probability of being selected (Starnes, Yates, & Moore, 2012). To determine the sample size, the Krejcie & Morgan (1970) table was utilized. The population of this research consisted of 17 school principals from 19 cycle 2 and 3 public schools, as two schools are currently without a formal principal. The sample size was determined to be 16 school principals, to generate a margin of error of ± 5% with a confidence of 95%, based on the Krejcie and Morgan formula and table (Krejcie & Morgan, 1970).

The research instrument used was the SP-DDL questionnaire, which was adapted based on the AIF framework from the DDDM-Q and EC-DDDM instruments used and verified in several research projects (Goodwin, 2002; Barton, 2019; Barton & Akin, 2022; Carpenter, 2017; Hinkin, Tracey, & Enz, 1997). The SP-DDL instrument was presented to a panel of five reviewers, chosen for their diverse knowledge backgrounds relevant to the research subject. They provided feedback on adjusting for suitability to Al Dhafra public schools. Next, a pilot study was conducted with five participants from school leadership teams in the Al Dhafra region. Based on their responses and recommendations, the questionnaire was reviewed and amended. The SP-DDL questionnaire is composed of three main parts, with the first collecting participants' demographic information. The second part contains nine Likert scales, corresponding to the nine AIF-Drivers, which are subcomponents of three main construct levels (Competency drivers, Organization drivers, Leadership-drivers). The items related to each factor were grouped in each scale. The statement was rated on a 5-point Likert-style scale, with 1 indicating Strongly Disagree, 2 indicating Disagree, 3 indicating Neither Agree nor Disagree, 4 indicating Agree, and 5 indicating Strongly Agree. The questionnaire constructs are explained in Table 1.

Table 1. SP-DDL questionnaire construct.

Construct-level model(3 factors)	Subcomponent driver level model(9 factors)	Number of items
Competency. drivers	Selection	5
	Training	7
	Coaching	6
	Performance-assessment	4
Organization. drivers	Systems-intervention	6
	Facilitative administration	8
	Decision-support data-systems	7
Leadership. .drivers	Technical	6
	Adaptive	5

The researcher collected quantitative data from the school leader questionnaire using a Google Form with Likert scales. In preparation for analysis on SPSS software, the researcher converted respondents' answers from words like "Strongly Agree" to numbers like "5". After organizing the data for import into IBM SPSS, the researcher extracted the necessary data from the original file, based on the research questions and the scale used. This step was crucial in ensuring the accuracy and validity of the data for the analysis step. The researcher utilized descriptive analytics to determine how school leaders in Al Dhafra region Cycle 2 and 3 public schools rated their school's readiness for DDL. The frequency means and standard deviations for each item were calculated using SPSS version 27 (IBM Corporation, 2021).

Pilot Study

The researcher conducted a pilot study with a sample of five School Leadership Teams (SLTs). These SLTs represent a diverse sample, as they are all school leaders working in UAE public schools. The pilot study was conducted using Google Forms as the means to distribute and fill out the questionnaire with the SLTs. The researcher directly observed five of the SLTs as they completed the questionnaire using a Google Meet video call. All notes and obstacles faced by the SLTs were recorded by the researcher, along with any observations he made. Additionally, participants were asked to share their notes on the questionnaire using a form that was shared with them. The researcher analyzed the internal consistency of the questionnaire by calculating Cronbach's Alpha for both the nine and three-factor models. For the nine-factor model, seven of the nine factors surpassed Nunnally's (1978) suggested minimum level of α=0.7, with two factors, staff-selection and performance assessment, barely falling below this level (with α= 0.68 and α= 0.69, respectively). For the three-factor model, all three factors showed high internal consistency, with Cronbach's Alpha values ranging from 0.831 to 0.92. The overall Cronbach's Alpha (α) for the entire questionnaire was 0.976, indicating excellent internal consistency, as established by Konting, Kamaruddin, & Man (2009).

Data Analysis

The analysis of how school leaders in Al Dhafra region Cycle 2 and 3 public schools rated their school's readiness for DDL involved assessing the responses of school principals to 54 items on the School Principal Data-Driven Learning (SP-DDL) questionnaire. Responses were measured on a 5-point Likert Scale from 1 to 5 (Strongly Disagree to Strongly Agree). To ensure scores reflected a higher use of data, three items were reverse-scored: selection 3, performance assessment 4, and decision-support 5. Descriptive analyses were carried out using SPSS (IBM Corporation, 2021). Descriptive statistics, including the number of participants, means, standard deviations, and frequencies, are provided for each item in Appendix A. An example of the data analysis for the first AIF driver is presented in Table 02.

Table 2. Descriptive analysis for Staff selection and hiring driver.

Survey item		N	M	SD	Strongly-Agree n (%)	Agree n (%)	Neither Agree nor Disagree n (%)	Disagree n (%)	Strongly-Disagree n (%)
Staff Selection & Hiring	1	16	4.19	0.655	5(31.25)	9(56.25)	2(12.5)	0(0)	0(0)
	2	16	4.13	0.619	4(25)	10(62.5)	2(12.5)	0(0)	0(0)
	3	16	3.69	1.014	3(18.8)	8(50)	2(12.5)	3(18.8)	0(0)
	4	16	4.00	0.730	4(25)	8(50)	4(25)	0(0)	0(0)
	5	16	4.06	0.680	4(25)	9(56.3)	3(18.8)	0(0)	0(0)

Participants responded to the 54 individual items of the SP-DDL questionnaire, with response ranges spanning from 1.0 to 5.0. Overall, the descriptive statistics showed principal agreement, with 52 of the 54 items having mean scores of 3.5 or higher. The lowest-scoring item was "school supervisors use their own discretion to evaluate the performance of individual staff members" (M=2.88, SD=1.088), while the highest mean score was "Our school will improve if we continuously review school data" (M=4.75, SD=0.447). This suggests that the majority of participants showed small, medium, or high levels of agreement with the items, indicating a belief that their schools are effectively implementing DDL. Moreover, descriptive statistics revealed that most participants believed their schools had generally achieved an important stage of DDL, with 51 out of 54 questionnaire items scoring 3.5 or above. This indicates that respondents showed medium, moderately high, and high levels of agreement with the items.

Results

The SP-DDL questionnaire was used to assess respondents' perceptions of the nine Drivers in their schools. For each of the nine AIF subscales in the questionnaire, two index scores were calculated. The summative index score was determined by summing up the items corresponding to each subscale. By dividing the summative index score by the number of items in each subscale, we were able to standardize comparisons and analyses across subscales. On a fivepoint scale, the lowest possible mean-per-item index score is 1.0, and the highest is 5.0. Descriptive statistics for each subscale are provided in Table 3. All subscales had a mean score of 3.5, indicating overall agreement among respondents. Adaptive leadership received the highest score (M=4.24, SD=0.586), while staff selection received the lowest (M=4.01, SD=0.74). According to the subscale scores, respondents generally agreed that their schools were successful in terms of the nine drivers, with all subscales scoring above 3.5.

Table 3. Summative and mean per item Index Score

Subscale	N	Mean Summative Index Score	Std Dev.	Mean per Item Index Score	Std Dev	Rank*
Staff & Selection & Hiring	16	20.06	3.699	4.01	0.740	7th
Training	16	29.69	3.878	4.14	0.640	5th
Coaching & Supervision	16	24.94	3.765	4.14	0.636	5th
Performance Assessment & Performance Evaluation	16	15.50	3.040	4.10	0.656	6th
Systems Intervention	16	26.13	3.078	4.15	0.629	4th
Facilitative administration	16	35.19	5.842	4.20	0.649	2nd
Decision support data system	16	27.69	5.148	4.16	0.661	3rd
Technical Leadership	16	25.00	3.942	4.16	0.661	3rd
Adaptive leadership	16	21.19	2.932	4.24	0.586	1st

*Note: Rankings based on the highest to lowest.

The internal consistency of the research tool was evaluated by determining Cronbach's Alpha (α) for both the nine and three-factor models. Seven of the nine factors in Nunnally's (1978) model exceeded the desired threshold for a satisfactory level. The remaining factors, staff selection, and performance assessment, barely fell below this threshold (with α=0.678 and α=0.660, respectively). In the three-factor model, all three factors showed high internal consistency, with a Cronbach's Alpha value of 0.976. The overall Cronbach's Alpha (α) for the entire questionnaire was also 0.976, demonstrating excellent internal consistency.

Discussions

According to the SP-DDL survey results, school principals generally agree that DDL is important for their schools. On average, respondents agreed with 52 out of 54 items, demonstrating that school principals recognize the value of using data to support DDL in their schools. The other two items received moderately neutral responses, with scores of 2.88 and 2.99. These scores fall in the range of 2.61 to 3.40, indicating a response of "Neither Agree nor Disagree." This suggests that school leaders largely agree with data use and the underlying competencies, organizational structures, and leadership concepts ingrained in DDL. These topics are familiar to school principals, indicating a possible transition from the pre-contemplative phase of change (DiClemente et al., 2014) and openness to DDL. Furthermore, understanding school readiness for DDL and delving into its implications may require connecting these findings to various change theories. This also ties into Theme 11 (Leadership Style and Change Model), derived from the first research phase.

The researcher presented two notable findings regarding the highest-ranking subscales. In the organizational construct of the AIF-Drivers framework, the adaptive-leadership scale and the facilitative-administration scale received the highest scores. This may reflect the pressure principals face in documenting school success, indicating that leaders understand the importance of demonstrating accountability, ongoing quality improvement, and effectiveness (Zweig, Irwin, Kook, & Cox, 2015). Additionally, the lowest-scoring subscales included: performance assessment, staff selection, coaching, and training drivers. Which are all competency-based. Consequently, school leaders may view hiring, training, and ongoing performance monitoring with less emphasis on compliance.

Consequently, there may be opportunities for integrating data into these processes which warrant further exploration. Two subscales related to the leadership construct consistently ranked in the middle. The decision-support data-system and technical-leadership subscales were positioned in third place. This suggests that school principals may identify more with the management functions of DDL rather than the transformational leadership functions, as concluded by Guerrero, Frimpong, Kong, Fenwick, & Aarons (2018). This research did not explain why school principals prioritized their facilitative-administration and adaptive-leadership roles over their technical-leadership roles when it came to DDL. It could be because they perceived the facilitative and adaptive roles as more conducive to the effective implementation of DDL.

Alternatively, the technical roles may have been seen as requiring more traditional leadership approaches, making DDL less of a priority. The higher ratings of the systems-intervention, administrative-facilitation, and decision support systems subscales may be due to the participants' familiarity with the responsibilities of school principals and their correlation with DDL. On the other hand, the lower responses on the technical items could be a result of participants lacking sufficient experience with DDL or associating it with the duties of top executives. As implementation frameworks stress the importance of strong leadership for successful change (Lyons, Timmons, Cohen-Hall, & LeBlois, 2018), more research is needed to identify the specific roles of leadership in the context of education and DDL measures. Furthermore, in the organization-construct subscales, the decision-support data-systems subscale ranked third, placing it in the middle, while the other subscales ranked higher.

Conclusion

Adopting data to indicate learning efficacy, designating cues of responsibility, and executing evidence-based interventions are increasingly demanded in educational systems (Coulton, Clift, Skingley, & Rodriguez, 2015). While there is a wealth of literature to suggest that the utilization of DDL in schools can support change (Dill & Shera, 2015), the use of data in schools for advising policy decisions and practices is still in its infancy (Coulton, Clift, Skingley, & Rodriguez, 2015). In particular, schools are required to utilize data to facilitate DDL, yet there is limited research as to the most effective ways to utilize data and the ability to gather and analyze data in practices that reinforce DDL, both globally (Yazejian & Bryant, 2013) and in the UAE context (Ghrier, 2022). The definition of DDL is more than the type of data collected, the way it is stored, or the method of analysis; the process involves a detailed understanding of the interactions between staff competence, organizational structure, and leadership dynamics inside a school (Zweig, Irwin, Kook, & Cox, 2015).

This research aspired to expand comprehension regarding DDL. These efforts resulted in identifying the AIF and its drivers as a suitable framework for understanding DDL in schools and using associated research instruments to study how school principals in Al Dhafra public cycle 2 and 3 public schools rate their school readiness for implementing DDL. According to the study's findings, an instrument based on nine different AIF drivers may provide an initial framework to understand how DDL is implemented in schools. The findings are particularly noteworthy in light of existing theory and practical literature and recent calls for more rigorous measurement. Using the three model drivers of the AIF, school principals rated their school readiness. In the group that scored the highest, organizational-drivers related to systems-intervention, decision-support data-systems, and facilitative-administration were prevailing, suggesting that principals essentially comprehend the significance of data. The group with the lowest score primarily consisted of competency-driver items.

This finding indicates that in both hiring and training processes, as well as in coaching and performance assessment, there is a lower preparedness for DDL. Additionally, some leadership drivers were rated between the middle and upper levels, contributing to an ambiguous readiness for DDL at the leadership level. Overall, this classification also confirms that schools function within complex and multilevel systems (Weiner, 2019). The researcher concludes that the findings of this research will support school principals and other educational leaders as they implement DDL in their schools. Additionally, it will allow them to understand their needs related to DDL readiness as they encounter an increasing necessity to use data to reinforce DDL and promote successful implementations. Moreover, the tool will provide researchers with a research-based instrument for studying DDL in schools.

Limitations and Future Studies

After conducting the study and discussing the findings, limitations were identified. These limitations can be categorized into different contexts. Firstly, this was a prevalence study with no evidence of SP-DDL's effectiveness over time. The study cannot determine how DDL readiness varies over time or how implementation drivers change during the implementation duration. In some cases, the implementation process can be lengthy, and the use of SP-DDL questionnaires multiple times could support test-retest reliability and aid in recognizing patterns in these tendencies. Secondly, this study is limited in two ways. Firstly, the data collected through self-report surveys may be prone to bias due to respondents' perceptions, attitudes, and beliefs towards DDL. Secondly, the sample size was deemed sufficient, but it was restricted to school principals in the Al Dhafra region public schools. The study could benefit from recruiting participants on a national level, including individuals from different levels of the school hierarchy such as school vice principals, academic principals, department heads, teachers, administrative leaders, and students' guardians. This could provide a more diverse perspective on data practices in UAE public schools.

Thirdly, This study used a quantitative questionnaire design, which was necessary but resulted in limited commentary on the reasons for the results. To understand why school principals rated certain factors or items more strongly than others, researchers should combine their responses to the SP-DDL questionnaire with qualitative data from interviews and other resources. This will also help researchers understand how scores on different factors are related. Fourthly, The researcher chose a small panel to review the final instrument due to limitations of time and availability. In recruiting panel members for similar studies, researchers should consider these limitations and involve panelists in subsequent instrument development iterations while ensuring they are compensated. Lastly, while the internal structure of the SP-DDL questionnaire may provide important evidence regarding its validity, caution must be taken when relying solely on this type of evidence. This research provides preliminary evidence supporting the validity of the SP-DDL questionnaire and suggests that the AIF-Drivers can measure school readiness. However, there are still many unanswered questions that need to be explored.

Further research is required to gain a better understanding of the various roles of school leaders in DDL, and to incorporate more leadership positions from the SLT teams in schools, such as VP and AVP. One suggestion for future research would be to conduct a comparative study that examines student performance and learning outcomes in schools that have implemented DDL versus those that have not. Additionally, further research could investigate the factors that contribute to the successful implementation of DDL in schools. Moreover, research should be conducted to explore the strategies for successful DDL implementation, including those for engaging teachers and other staff in DDL, as well as the role of data coaches and data champions. Furthermore, the impact of DDL on teacher motivation and job satisfaction could be studied by exploring the role of data use and DDL in improving school culture and climate. By conducting additional research, a better understanding of DDL's role in education can be gained.

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Appendix A

Table A1. School principal questionnaire Variables, Survey Items, and Descriptive Statistics (N=16)

Survey item		**N**	**M**	**SD**	**Strongly- Agree n (%)**	**Agree n (%)**	**Neither Agree nor Disagree n (%)**	**Disagree n (%)**	**Strongly-Disagree n (%)**
Staff Selection & Hiring	1	16	4.19	0.655	5(31.25)	9(56.25)	2(12.5)	0(0)	0(0)
	2	16	4.13	0.619	4(25)	10(62.5)	2(12.5)	0(0)	0(0)
	3	16	3.69	1.014	3(18.8)	8(50)	2(12.5)	3(18.8)	0(0)
	4	16	4.00	0.730	4(25)	8(50)	4(25)	0(0)	0(0)
	5	16	4.06	0.680	4(25)	9(56.3)	3(18.8)	0(0)	0(0)
Training	1	16	4.38	0.500	6(37.5)	10(62.5)	0(0)	0(0)	0(0)
	2	16	4.13	0.806	5(31.3)	9(56.3)	1(6.3)	1(6.3)	0(0)
	3	16	4.19	0.544	4(25)	11(68.8)	1(6.3)	0(0)	0(0)
	4	16	4.19	0.655	5(31.3)	9(56.3)	2(12.5)	0(0)	0(0)
	5	16	4.25	0.447	4(25)	12(75)	0(0)	0(0)	0(0)
	6	16	4.25	0.447	4(25)	12(75)	0(0)	0(0)	0(0)
	7	16	4.31	0.479	5(31.3)	11(68.8)	0(0)	0(0)	0(0)
Coaching & Supervision	1	16	4.13	0.619	4(25)	10(62.5)	2(12.5)	0(0)	0(0)
	2	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)

	3	16	4.19	0.750	6(37.5)	7(43.8)	3(18.8)	0(0)	0(0)
	4	16	4.00	0.730	3(18.8)	11(68.8)	1(6.3)	1(6.3)	0(0)
	5	16	4.19	0.544	4(25)	11(68.8)	1(6.3)	0(0)	0(0)
	6	16	4.19	0.544	4(25)	11(68.8)	1(6.3)	0(0)	0(0)
Performance Assessment & Performance Evaluation	1	16	4.13	0.806	5(31.3)	9(56.3)	1(6.3)	1(6.3)	0(0)
	2	16	4.19	0.544	4(25)	11(68.8)	1(6.3)	0(0)	0(0)
	3	16	4.31	0.602	6(37.5)	9(56.3)	1(6.3)	0(0)	0(0)
	4	16	2.88	1.088	2(12.5)	2(12.5)	4(25)	8(50)	0(0)
System Intervention	1	16	4.31	0.602	6(37.5)	9(56.3)	1(6.3)	0(0)	0(0)
	2	16	4.50	0.516	8(50)	8(50)	0(0)	0(0)	0(0)
	3	16	4.38	0.500	6(37.5)	10(62.5)	0(0)	0(0)	0(0)
	4	16	4.56	0.512	9(56.3)	7(43.8)	0(0)	0(0)	0(0)
	5	16	4.25	0.447	4(25)	12(75)	0(0)	0(0)	0(0)
	6	16	4.13	0.500	3(18.8)	12(75)	1(6.3)	0(0)	0(0)
Facilitative Administration	1	16	4.06	0.854	5(31.3)	8(50)	2(12.5)	1(6.3)	0(0)
	2	16	4.50	0.632	9(56.3)	6(37.5)	1(6.3)	0(0)	0(0)
	3	16	4.19	1.047	8(50)	5(31.3)	1(6.3)	2(12.5)	0(0)
	4	16	4.31	0.873	8(50)	6(37.5)	1(6.3)	1(6.3)	0(0)
	5	16	4.63	0.500	10(62.5)	6(37.5)	0(0)	0(0)	0(0)

	6	16	4.50	0.632	9(56.3)	6(37.5)	1(6.3)	0(0)	0(0)
	7	16	4.75	0.447	12(75)	4(25)	0(0)	0(0)	0(0)
	8	16	4.25	0.856	7(43.8)	7(43.8)	1(6.3)	1(6.3)	0(0)
Decision Support Data System	1	16	4.38	0.500	6(37.5)	10(62.5)	0(0)	0(0)	0(0)
	2	16	4.50	0.516	8(50)	8(50)	0(0)	0(0)	0(0)
	3	16	2.94	0.929	0(0)	5(31.3)	6(37.5)	4(25)	1(6.3)
	4	16	3.75	1.000	4(25)	6(37.5)	4(25)	2(12.5)	0(0)
	5	16	3.94	0.772	3(18.8)	10(62.5)	2(12.5)	1(6.3)	0(0)
	6	16	3.94	0.854	4(25)	8(50)	3(18.8)	1(6.3)	0(0)
	7	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
Technical Leadership	1	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
	2	16	4.00	0.816	4(25)	9(56.3)	2(12.5)	1(6.3)	0(0)
	3	16	4.00	0.816	4(25)	9(56.3)	2(12.5)	1(6.3)	0(0)
	4	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
	5	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
	6	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
Adaptive Leadership	1	16	4.31	0.479	5(31.3)	11(68.8)	0(0)	0(0)	0(0)
	2	16	4.19	0.655	5(31.3)	9(56.3)	2(12.5)	0(0)	0(0)

	3	16	4.31	0.602	6(37.5)	9(56.3)	1(6.3)	0(0)	0(0)
	4	16	4.25	0.577	5(31.3)	10(62.5)	1(6.3)	0(0)	0(0)
	5	16	4.13	0.619	4(25)	10(62.5)	2(12.5)	0(0)	0(0)

*Note: Items selection3, perf-assess4, and decision-support3 were reversed scored.