Development of a Model for Data-Driven Decision Making: Critical Skills for School Leaders

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ABSTRACT

Data may equip school leaders with the information they need to make crucial changes that will enhance the education system in the future although the usage of data may not be able to resolve every issue. However, proper data utilization can advise the right conclusion. Therefore, this study aims to design and develop an experiential narrative-based model for school leaders in data-driven decision-making (DDDM). The model has been designed and developed using the Design and Development Research (DDR) approach, which involves three phases: the need analysis phase, the design and development phase, and the usability evaluation phase. However, the researcher only focuses on this paper in the second phase. The design and development process began with a literature study, followed by approval and consensus from a 9-expert panel. The model was designed using the Nominal Group Technique (NGT) technique and developed using the Interpretive Structural Modelling (ISM) method. The design and development phase revealed that 13 DDDM competency components had been generated through the expert panel’s opinions and agreement. Overall, based on the experiential narrative of the experts in this study, the model is appropriate for usage and implementation. As a result, the empirically established and verified model has the potential to enhance school leaders’ knowledge, skills, and attitudes toward data-driven decision-making.

Contribution/Originality: This study contributes to the educational leadership context by proposing a novel model for school leaders in data-driven decision making (DDDM). In general, the results emphasize the importance of leaders enhancing their competencies when it comes to DDDM. It also emphasizes the significance of improving decision making processes and achieving educational outcomes.

1. Introduction

Since the world has entered the fourth industrial revolution era, there has been an increase in the amount of digital data that is being generated, collected, and stored
(Ashaari et al., 2020; Akal et al., 2019; Mokhtar et al., 2019; Cech et al., 2018). This massive volume of data has necessitated organizations at all levels to develop innovative approaches for making decisions based on data (Yang & Bayapu, 2019). As a result, the digital revolution has paved the way for the adoption of data-driven decision making (DDDM) across industries such as telecommunications, commerce, agriculture, healthcare, and education (Jannah Talib & Fariza Khalid 2020; Akal et al., 2019; Mokhtar et al., 2019; Yang & Bayapu, 2019). In times, DDDM has become a topic of debate when it comes to initiatives for improving schools’ performance. However how exactly do school leaders and teachers utilize data to enhance school performance?

Previous research has highlighted challenges associated with decision making. These include the tendency to overlook standing issues relying on instinct when making choices difficult, distinguishing between important and less important decisions, and a lack of adaptability in the decision-making process (Kowalski et al., 2008). Moreover, the significance of utilizing data is often. Many school leaders lack the tools and expertise to effectively utilize it (Hubers et al., 2017). This situation arises because existing studies do not offer a foundation, for understanding how to develop the knowledge and skills required for DDDM (Bulkley & McCotter, 2017).

Consequently, school leaders must possess knowledge, skills, and abilities such as data literacy. This enables them to monitor and foster a data-driven culture in the workplace (Ashaari et al., 2020; Luhukay et al., 2019; Athamena & Houhamdi, 2018; Zulkvan Geel et al., 2018). The significance of school leaders in influencing the utilization of data to enhance success and delivery effectiveness is obvious (Bulkley & McCotter, 2017). Despite the benefits that data can provide in decision making processes in the field of education, its implementation still faces various challenges (Akal et al., 2019; Wang, 2019; Adrian et al., 2018; Bogdan & Lungescu, 2018). Therefore, it is crucial to evaluate competence in DDDM to prevent outcomes in the future. Thus, this article presents findings on DDDM competencies derived from consensus using both the Nominal Group Technique (NGT) and Interpretive Structural Modeling (ISM) methods.

1.1. Research Objectives

The study aims to accomplish the following objectives;

i. To identify the competencies required for effective data-driven decision making through expert consensus.

ii. To propose a competency model prototype for data-driven decisions making through expert consensus.

2. Literature Review

2.1. Data-Driven Decision Making in Education

Data-Driven Decision Making (DDDM) in the world of education is a generic process that involves the systematic collection and analysis of data by teachers, principals, and administrators (Hamilton et al., 2009; Ikemoto & Marsh, 2007; Marsh et al., 2006). This process not only helps to improve student and school performance but also provides insights, into the practices and policies of educational organizations (Mandinach, 2012). In fact, using statistics and empirical data analysis can aid in decision making by identifying problems and planning strategies to enhance performance, reduce expenses, and allocate resources efficiently (Custer et al., 2018).
From the perspective of school leaders, DDDM is relevant at all levels of education and relies on statistical methods to make informed judgments. Over the years, the focus of DDDM has shifted from relying on assessment data and student achievement as outcome measures to encompassing a wide range of data sources such as classroom observations, student feedback, and parent surveys. Additionally, the outcome measures have expanded beyond just student achievement to include areas, like student learning and well-being (Mandinanch & Shildkamp 2020b).

In years, the significance of data and DDDM in education has grown due to the increasing focus on rigor as advocated by the US Department of Education in both practice and research. Simply relying on anecdotes, gut feelings or opinions is no longer deemed acceptable when making decisions (Mandinach, 2012). The use of data in education has also gained attention in the United States through initiatives like the No Child Left Behind Act of 2001 and the Every Student Succeeds Act of 2015. School leaders and teachers have been entrusted with the responsibility to implement DDDM for assessing student needs providing targeted support and planning school enhancements (Wayman et al., 2012). Therefore, school leaders play a role, in ensuring the adoption of DDDM within schools (Ikemoto & Marsh 2007; Schildkamp & Lai, 2013; Hallinger & Heck, 2011).

The education system is quite complicated, with levels that impose responsibilities and data requirements on leaders at each level. Hence understanding data can greatly assist school leaders in determining the efficient methods to achieve their objectives. When school data is collected and utilized effectively it can yield outcomes in terms of student learning and school improvement (Cech et al., 2018; Johnson & Kruse, 2009). According to Mandinach and Schildkamp (2020) implementing DDDM proficiently can also support school leaders and teachers in making equitable decisions.

Although there are opportunities with DDDM, there are challenges that need to be addressed. These challenges include the lack of data literacy and insufficient involvement of school leaders in the DDDM process (Wu, 2009). It is crucial to ensure that data is used correctly and effectively in making administrative decisions (Monaghan, 2017; Mandinach, 2012). It should be noted that incorrect application of data can lead to missed improvement opportunities and undesired outcomes, for school leaders and teachers (Cech et al., 2018). Hence it is essential to provide support and training to enable school leaders and teachers to develop their DDDM skills and commit to using data (Park & Desimone, 2019; Zulkvan Geel et al., 2018).

To summarize, the implementation of DDDM involves elements that can either support or hinder the effective and responsible utilization of data. This complexity makes it challenging to determine the effects of data use, on classroom instruction and student achievement (Mandinach & Shildkamp 2020b).

2.2. Experiential Narrative in Semi-Quantitative Research

Experiential narrative in semi-quantitative research involves capturing subjective experiences through a qualitative approach, blending narrative elements with semi-quantitative methodology. This approach involves analyzing how individuals recount events in their lives to gain insight into the meaning and purpose they create (Chua, 2022; McAdams, 2008). The use of narratives is valuable in various fields and subjects as they provide a comprehensive and nuanced understanding of individuals’ beliefs and
encounters. Whether it’s in education (Danko, 2019), medicine (Halloy et al., 2022), counseling (Soroko, 2021), or social sciences that incorporate a narrative perspective, throughout the research process.

Meanwhile, qualitative data involves the interpretation of information which allows researchers to gain an understanding of the phenomenon being studied. It can be challenging to comprehend behavior, characteristics, and environmental contexts through numerical analysis. Therefore, researchers employ methods to collect research data, such, as observation, interviews, and document analysis (Chua, 2022). In this regard, narrative approaches used in focus group discussions offer a perspective on the experiences of academics. They contribute by extracting information about topics, generating hypotheses evaluating instruments and programs, or providing a better explanation for the range and depth of attitudes, beliefs, and experiences, within a specific population (Seal et al., 1998).

Moreover, the nominal group technique (NGT) is widely acknowledged as a semi-quantitative evaluative method. This approach employs a group discussion to address problem-solving and decision making striking a balance, between qualitative approaches (Perry & Linslay, 2006). The effectiveness of NGT in facilitating group discussions has been well established (Olsen, 2019). By incorporating expert narratives, NGT enhances the depth and relevance of these discussions by providing real-world insights. Consequently, the semi-quantitative nature of NGT proves invaluable in gathering insights, within a structured decision making framework.

Furthermore, researchers often rely on interviews when they need to gather information within a timeframe (Noraini, 2013). To do so, the researcher prepares a checklist or a set of questions about the area of study. During the interview process, the researcher can extract information that aligns with the study’s objective. However, it's important to note that narratives don't simply occur spontaneously; they involve stages, in research development that require attention. Initially, data is collected by conducting structured interviews which allow participants to share their personal experiences in an informal and comfortable setting. The subsequent stages involve shaping the narrative based on field text and conducting narrative analysis (Pepper & Wildy, 2009).

Despite the benefits, it offers incorporating expert narratives requires an approach that considers such as group dynamics, potential biases, and the need, for representation of experts. By that, the expert narratives within the NGT framework offer an approach to gathering data and building consensus. Combining a methodology, with real-world expertise enhances the credibility and practicality of research outcomes.

3. Research Methods

The second stage of a Design and Development Research (DDR) study holds importance as it involves the creation and development of the model (Richey & Klein, 2014). In this study, researchers utilized a combination of the Nominal Group Technique (NGT) and Interpretive Structural Modelling (ISM) methods to gather consensus on the competencies required for school leaders in DDDM. The decision to employ both NGT and ISM methods during the second phase was based on their compatibility (Georgekopoulus, 2009; Janes, 1988). Additionally, it is worth noting that the NGT method is commonly used in the step of implementing the ISM method well (Saedah Siraj et al., 2021). Hence combining these two methods was deemed suitable. Complemented each other
effectively. The semi-quantitative data collection involved specialists and experts, in education administration and leadership who were affiliated with universities and the Malaysian Education Ministry. This competency aims to enhance school leaders’ skills in Malaysia in the future.

### 3.1. Nominal Group Technique

Nominal Group Technique (NGT) is a decision making process commonly employed by expert groups (Delbecq et al., 1971). It involves the equal participation of all members, where everyone’s input holds weight and importance (Delbecq et al., 1971). NGT serves as a method for brainstorming and generating ideas to address issues or problems and create a defined framework (Dang, 2015). Dobbie et al. (2004) also described NGT as an approach to facilitate problem solving among experts enabling them to reach a consensus on matters and produce high-quality recommendations and solutions. Furthermore, the data collection process, in NGT is both semi-quantitative and structured (Dobbie et al., 2004; O’Neil & Jackson, 1983). This means that it begins with sharing ideas followed by prioritizing those ideas (O’Neil & Jackson, 1983).

The NGT approach offers benefits when applied in research. According to Van De Ven and Delbecq (1971) and Delp et al. (1977), the NGT method possesses six strengths, including:

- a) It allows for the generalization of opinions, across fields.
- b) Experts can engage in face-to-face discussions that focus on the issues under study. This fosters accurate resolutions while promoting universal characteristics by eliminating dominant biases.
- c) The method incorporates an idea generation phase where experts are encouraged to express their ideas without criticism or interruption from participants.
- d) All ideas that arise during the process are diligently recorded to prevent any loss of valuable insights.
- e) A discussion phase is included to provide explanations and minimize misunderstandings among experts.
- f) The NGT method enhances expert creativity by allowing each panel member the freedom to present arguments and generate ideas based on their experiences and creative thinking.

While the NGT technique does offer a chance to balance the roles of all participants it’s often quite challenging to achieve. This is mainly because every discussion process naturally tends to have a person who influences the outcome. When one or more participants hold sway, it can negatively impact the quality and fairness of the discussion (Denscombe, 1995; Watts & Ebbutt, 1987). To address this challenge conducting research that incorporates face-to-face and group discussions can be a solution.

Over time this approach has evolved while still maintaining its core principle of problem identification through debate and a voting procedure at the end of a group study. Scholars generally agree on five phases for implementing the NGT approach. In this study of brainstorming the researcher conducted a literature review to identify research challenges or issues. Step 2 was modified to transform this study into a version of NGT similar to the studies conducted by Dahlmann-Noor et al. (2023), Abdul Muqsith (2018), and Mohd Ridhuan (2016). Once the literature mapping is completed the initial updated list serves as a guide during the NGT workshop session to save time. However, it’s important to note that during this session additional ideas can still be discussed by the
expert panel, and they have the freedom to accept or reject items from the list. Hence the final list considers the competency components that experts agree upon before proceeding with the voting process. Figure 1 illustrates the flowchart for the revised NGT session.

Figure 1: Flowchart of modified NGT session for this study

3.2. Interpretive Structural Modelling

The method known as Interpretive Structural Modelling (ISM) was introduced by Warfield (1974) in 1974. What makes ISM stand out is its unique approach, to systematically solving complex problems. It relies on the insights and opinions of a group of experts in a field of study (IPGKDA, 2023; Mohd Ridhuan & Nurulrabihah, 2020). Moreover, ISM can process and transform expert panel ideas and opinions into visual representations, with the aid of computer software (IPGKDA, 2023; Mohd Ridhuan & Nurulrabihah, 2020; Sage, 1977; Warfield, 1974). This versatility positions ISM as a decision making tool that’s well suited for developing models (Mohd Ridhuan & Nurulrabihah, 2020; Jadhav et al., 2015). According to Mohd Ridhuan and Nurulrabihah (2020) several advantages have been identified for the ISM method. These include providing researchers with the ability to determine all elements related to the problem being studied, such as:

a) Allowing the expert panel to thoroughly examine and delve into each element through discussions.

b) Being adaptable and self-reliant capable of being utilized in scenarios.

The ISM approach consists of eight steps incorporating the NGT method in the stage as commonly practiced (Saedah Siraj et al., 2021). The researcher has modified the research procedure previously employed by Mohammad Ridhuan Tony Lim Abdullah (2014) and Abdul Muqsith (2018) to formulate their research model. Consequently, Figure 2 presents a flow chart illustrating the data collection process for this study.
3.3. Panel of Experts

The online workshop session, on NGT (Nominal Group Technique) and ISM (Interpretive Structural Modeling) was conducted using the Google Meet application. It involved a group of 9-experts panel representing five stakeholder groups, including lecturers from IPTA specializing in education and DDDM, leadership lecturers from IAB, state education officers, district education officers, and secondary school principals. The participants were selected using a purposive sampling strategy. This approach is commonly used in research when the number of participants is limited and it is important to ensure that the sample represents primary characteristics as much, as possible.

4. Results

4.1. Identifying Problems or Issues (NGT Method)

During the NGT workshop session, the expert panel was presented with a draft list of competency components for DDDM. The draft list of competency components was obtained through a study of existing models and a literature review related to DDDM. This draft list includes competencies such as digital literacy, data literacy, decision making, technical skills in data analytics, ecosystem culture, strategic thinking, critical thinking, communication, collaboration, change management, creativity and innovation, emotional intelligence, and integrity. The expert panel participated in a discussion to refine and finalize these components based on their relevance to the research context. Therefore, it is crucial to have the input of an expert narrative throughout this debate phase to finalize the components.

After the expert panel engaged in a discussion, they agreed to develop the competencies model in DDDM by combining the 13 competency components suggested at this stage. These 13 selected components were thoroughly improved in terms of terminology and language by the expert panel.

Following the selection process of DDDM competency components, each expert panel member was provided with questionnaires via Google Forms to ensure data validity and
reliability. This individual voting process aimed to re-evaluate all the components that were debated during the NGT workshop session.

The following table (Table 1) presents the results obtained from analyzing the DDDM competency components agreed upon by the expert panel using NGT. Additionally, Table 1 includes scores, percentages, and preferences based on voting results. The voting was conducted using a 7-point Likert scale ranging from strongly disagree to strongly agree. Components with scores of 70% or higher were considered accepted and suitable (Dobbie et al., 2004; Deslandes et al., 2010).

Table 1: Findings of the NGT Voting Session

<table>
<thead>
<tr>
<th>Components of DDDM Competencies</th>
<th>Experts</th>
<th>Score</th>
<th>Percentage (%)</th>
<th>Status</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital Literacy</td>
<td>E1: 7</td>
<td>58</td>
<td>92.1</td>
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</tr>
<tr>
<td>Data Literacy</td>
<td>E2: 6</td>
<td>58</td>
<td>92.1</td>
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<td>1</td>
</tr>
<tr>
<td>Decision Making</td>
<td>E3: 6</td>
<td>58</td>
<td>92.1</td>
<td>Accepted</td>
<td>1</td>
</tr>
<tr>
<td>Data Analytics</td>
<td>E4: 6</td>
<td>57</td>
<td>90.5</td>
<td>Accepted</td>
<td>4</td>
</tr>
<tr>
<td>Digital Ecosystem Culture</td>
<td>E5: 7</td>
<td>57</td>
<td>90.5</td>
<td>Accepted</td>
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<tr>
<td>Strategic Thinking</td>
<td>E6: 7</td>
<td>53</td>
<td>84.1</td>
<td>Accepted</td>
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<tr>
<td>Critical Thinking</td>
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<td>84.1</td>
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<td>82.5</td>
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</tr>
<tr>
<td>Creativity And Innovation</td>
<td>E10: 5</td>
<td>52</td>
<td>82.5</td>
<td>Accepted</td>
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<tr>
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<td>52</td>
<td>82.5</td>
<td>Accepted</td>
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</tr>
<tr>
<td>Integrity</td>
<td>E12: 5</td>
<td>51</td>
<td>81.0</td>
<td>Accepted</td>
<td>13</td>
</tr>
</tbody>
</table>

4.2. Determine Contextual Relationships and Phrasal Relationships

To develop the model, the ISM method was implemented. During the ISM workshop session, the panel entered these 13 competency components into the Concept Star software. They were selected based on their agreed priority list (Saedah Siraj et al., 2021).
The ranked competency component is paired with the priority component following a similar pattern, for the main components throughout the ISM session as shown in Table 1.

To determine the priority of these built competency components in the models’ development context, the selection of contextual and relational phrases is done as part of ISM procedure. The expert panel has agreed upon using relational phrases during this session.

Contextual Phrases: To ensure efficient data-driven decision making among school leaders, it is crucial to consider these components...

Relational Phrases: Prioritizing COMPONENT ... should come before COMPONENT...

Once the contextual and relational phrases have been formed, the competency components are compiled and presented to the expert panel through the Concept Star software.

4.3. Complete the Matrix for Element Interaction and Generate the Model

The Concept Star software is designed to aid in the matching of competency components by conducting pair analysis. This analysis enables a panel of experts to carry out the voting process. The process is repeated until all the main components and elements are combined. After the completion of the voting process, an expert panel reaches a consensus resulting in a diagram known as a prototype model. Figure 3 displays the prototype model, for the outlined component using Concept Star software.

Figure 3: DDDM Competencies Prototype Model
4.4. Display of Models and Simulations

At this stage, the prototype model created with Concept Star software is presented to the panel for review and confirmation. The expert panel expressed satisfaction, with the displayed results during the review process. There were no adjustments made based on discussions, among experts. Furthermore, the panel of experts reached a consensus. It recommended utilizing a prototype model that focuses on the main components. This approach ensures a more organized representation allowing for visibility compared to incorporating the entire model element.

4.5. Reachability Matrix

The researcher then conducted an analysis, on the application of Cross Impact Matrix Multiplication for classification purposes. This analysis aimed to identify the variables that have an impact and dependency power before the classification process, in the developed prototype model, which was tailored to a specific group. As part of this study, a reachability matrix based on the prototype model was presented in Table 2.

Table 2: Reachability Matrix

<table>
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<tr>
<th>Components</th>
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</table>

Note: DP : Driving Power  PD : Power of Dependency

Afterwards, the reachability matrix that has been constructed is divided based on the degree of influence, in partitioning the reachability matrix. As a result, all competency components are dissected according to their reachability and antecedent sets to find the intersection between these two sets, for each component. This information can be seen in Table 3.

According to the data presented in Table 3, we determine the influence and strength of each component based on its reachability and the antecedent set through level translation. Overall, there are five levels of competence. Components 7 and 8 are classified as level 4 which’s the highest level while component 5 is categorized as level 1 at the lowest level. These findings align with the prototype model generated by Concept Star software, which starts with components 7 and 8 and concludes with component 5. Therefore, if the level and position of the components are rearranged to break down the reachability matrix, the hierarchy of SSIM is shown in Table 4.
### Table 3: Partition of Reachability Matrix

<table>
<thead>
<tr>
<th>Components</th>
<th>Reachability Set</th>
<th>Antecedent Set</th>
<th>Intersection</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1, 2, 3, 4, 6, 9, 11</td>
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<tr>
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<td>1, 2, 3, 4, 6, 9, 11</td>
<td>2</td>
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<tr>
<td>4</td>
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<td>1</td>
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<td>6</td>
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<td>1, 2, 3, 4, 6, 7, 8, 9, 10, 11</td>
<td>1, 2, 3, 4, 6, 9, 11</td>
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<td>7, 8, 10</td>
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<td>3</td>
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<tr>
<td>11</td>
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<td>1, 2, 3, 4, 6, 9, 11</td>
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<td>12</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>13</td>
<td>7, 8, 10, 12, 13</td>
<td>13</td>
<td>2</td>
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</tbody>
</table>

### Table 4: Component Ranking Level Based on Reachability Matrix

<table>
<thead>
<tr>
<th>Components</th>
<th>DDDM Competency</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Digital Ecosystem Culture</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>Digital Literacy</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>Data Literacy</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Decision Making</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>Data Analytics</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>Strategic Thinking</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>Collaborative</td>
<td>2</td>
</tr>
<tr>
<td>11</td>
<td>Creative and Innovative</td>
<td>2</td>
</tr>
<tr>
<td>13</td>
<td>Integrity</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>Change Management</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>Emotional Intelligence</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>Critical Thinking</td>
<td>4</td>
</tr>
<tr>
<td>8</td>
<td>Communication</td>
<td>4</td>
</tr>
</tbody>
</table>

### 4.6. Classification of Model

The classification of the model is the final step in the ISM process. It involves differentiating the components based on their power value, which determines whether they contribute as driving forces or dependency factors. According to Warfield (1974), the prototype model is divided into four groups: independent, linkage, dependent, and autonomous groups. This division helps to analyze the driving power and dependency power of each competency component. The model classification division is shown in detail in Figure 4.
According to Figure 4, the independent group consists of three components; critical thinking (7) communication (8) and change management (10). Which have high driving power but weak dependency power. Consequently, it is crucial to master the competencies in this group before tackling competencies. In the linkage group, there are seven components; digital literacy (1) data literacy (2) decision making (3) data analytics (4) strategic thinking (6) collaborative (9) and creative and innovative (11). These components exhibit both driving power and strong dependence, on each other. They serve as links between the dependent components. Moving on to component (5) digital ecosystem culture which belongs to the group; it may have weak driving power but exerts a significant influence on other components. Lastly in the group, emotional intelligence (12) and integrity (13) as driving forces with weak dependency power. This implies that these two components stand apart from others while remaining parts of the system.

5. Discussion

The study findings indicate that this competency component aligns, with the existing KOMPAS 2.0 Model by IAB (2020), which comprises five competency components; visionary (setting) instructional (digital ecosystem culture) operational resources (managing various data) personal qualities (integrity) and relationships (building networks and connections). The results of this competency component are further supported by the SLCMEduc4.0 Model by Tai and Omar (2019), which identifies integrity, communication, collaboration, critical thinking, creativity and innovation decision making, change management, digital literacy, and emotional intelligence as competencies that school leaders must master in the era of the fourth industrial revolution. Additionally, competencies such as data literacy (Dingelstad et al., 2022; Chen et al., 2020; Przybylski et al., 2017; Monaghan et al., 2017; Mandinanch et al., 2008; Johnson & Kruse et al., 2009) and data analytics (Ashaari et al., 2020; Dingelstad et al., 2019; Park & Desimone et al., 2019; Ghasemaghaei et al., 2019; Cech et al., 2019) are also important competencies to be considered when enhancing school leaders’ quality.
It is crucial to have designed components, in place for the competency model to serve as a guideline and successfully meet the needs of an organization (Li et al., 2020). This aligns with Mandinach (2012) perspective that the DDDM models is a generic model that school leaders can utilize to make informed managerial and administrative decisions within educational institutions. Therefore, establishing a competency model for data-driven decision making plays a role, in enhancing the effectiveness of decision making processes through leveraging data, information, and knowledge (Mandinach, 2012; Light et al., 2004).

The following discussion pertains to the connection, between each component of competency that has been established. Apart from creating a matrix of reachability grouping classification also offers an overview and comprehension of the indirect relationships among each component of competency. The level based relationship depicted in this model highlights that each component of competency holds a position that should be followed sequentially in a guided manner. As mentioned by Mohd Ridhuan and Nurulrabihah (2020) the lowest level signifies a component, with influence or strength while the same applies to its counterpart.

For instance, skills like critical thinking, communication and change management fall into the independent category. These competencies hold influence. Have relatively weak interdependencies. This suggests that mastering critical thinking and communication is crucial for controlling competency in DDDM. Hence it is necessary to prioritize the development of critical thinking skills before addressing communication competence and other competencies in groups.

Furthermore, it is worth mentioning that the reachability matrix table highlights the fact that critical thinking and communication competencies are at their highest level, which is level five. This discovery aligns with studies emphasizing the significance of critical thinking and communication skills in DDDM. For instance, a study carried out by the World Economic Forum (2020) in 2020 identified thinking as a skill for employees to thrive in their professional environments. The report emphasizes that as data volume and complexity continue to grow possessing critical thinking abilities becomes essential for success (World Economic Forum, 2020). Similarly, to another research study found communication skills to be vital when making decisions based on data. It further emphasized that successful DDDM heavily relies on concise and relevant communication, from decision makers (Hannah et al., 2019).

Hence, in the realm of decision making both critical thinking and effective communication play roles. Critical thinking aids in recognizing information and gaining a grasp of the problem at hand while communication allows for the exchange of valuable insights and recommendations, with others. Without possessing these skills, it becomes challenging to arrive at founded decisions backed by evidence and effectively convey them to stakeholders.

Regarding the linkage group it consists of seven competency components; digital literacy, data literacy, decision making, data analytics, strategic thinking, collaboration and creative and innovative. These components play a role, in driving and depending on each other. The linkage group serves as a connection between dependent components. Therefore, all competencies within this group act as links, among groups (Ahmad et al., 2019; Warfield, 1974). Consequently, any changes made to these components will directly
impact other competencies well. However, if we implement these competencies correctly, the DDDM competency model implementation will undoubtedly succeed.

This scenario differs from the digital ecosystem culture competency, which falls under the lowest tier of dependency component. While this component demonstrates driving force it heavily relies on elements, for its effectiveness. Consequently, implementing this aspect of digital ecosystem culture independently would not yield results (Nor Ayu, 2018). Thus, the cultural aspects of the digital ecosystem require support and cooperation from other components, within both linkage groups.

While cultivating a digital ecosystem can certainly assist in utilizing technology, it’s important to note that having such competence isn’t an absolute requirement, for making effective data driven decisions. A study conducted by McKinsey & Company discovered that the success of an organization in DDDM is closely tied to its organizational maturity rather than solely its level of digital advancement (Bughin & Hazan, 2018). Moreover, it’s worth considering that not every organization may find it feasible or suitable to establish an ecosystem culture. For instance, smaller organizations or those, with resources might not have the budget or expertise to invest in digital technology and skill development. Additionally certain organizations may face privacy concerns that restrict their use of specific technologies. Thus, while embracing a digital ecosystem culture might have its advantages in situations, it does not automatically ensure success, in the process of DDDM. Instead, organizations should focus on nurturing skills and capabilities that are crucial for making informed decisions based on data. To summarize it is vital to establish a connection between the components level and this competency element. This connection can serve as a guiding principle, for school leaders when implementing the DDDM process systematically within institutions.

Meanwhile in the autonomous group, the competencies of emotional intelligence and integrity have a significant influence but relatively low dependency, on the overall system. This implies that these elements have limited impact, on the system (Abdul Muqsith, 2018) and do not heavily affect the model (Nor Ayu, 2018). However, they still retain relevance and play their role, within the system (Ahmad et al., 2019).

6. Conclusion

In conclusion, this study demonstrates that proficiency in DDDM is widely recognized as a skill for school leaders to acquire. This is because school leaders have a responsibility in making decisions to address various issues (Vroom, 2000; Bishop, 2019; Wayman et al., 2012; Mandinach et al., 2006). Moreover, when these decisions are grounded in evidence and reliable data sources, they tend to be informative, efficient and trustworthy (Custer et al., 2018; Kowalski et al., 2008). Considering the significance and necessity of DDDM, this study has successfully developed a model to enhance the competencies of school leaders, in DDDM. As a result, it can be inferred that all 13 competencies outlined in the DDDM competency model can effectively aid academics in decision making within the context. Furthermore, this model is anticipated to augment the knowledge, skills and attitudes of academics towards DDDM while also positively impacting the efficacy of DDDM practices within education sector in Malaysia.
Ethics Approval and Consent to Participate

The researchers used the research ethics Educational Research Application System provided by the Research Ethics Committee of Education Planning and Policy Research Division (EPRD), Ministry of Education Malaysia. All procedures performed in this study involving human participants were conducted in accordance with the ethical standards of the ministry research committee.

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Conflict of Interest

The authors declare no conflicts of interest.

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Olsen, J. (2019). The Nominal Group Technique (NGT) as a tool for facilitating pan-disability focus groups and as a new method for quantifying changes in qualitative


