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Decision Management: A Missing Competency Area in Information Systems Curriculums

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Abstract

We introduce an important missing competency in Information Systems (IS) academic programs, namely decision management (DM). We demonstrate how DM plays a critical role in many IS activities such as the service-oriented programming paradigm. To provide evidence that DM is a missing competency, the paper presents an analysis of the course data from 23 top IS programs in the US which shows that the key elements of the DM discipline are not receiving sufficient emphasis or completely missing from the IS curricula. We urge that actions be taken to implement this key competency into IS programs and suggest several options to do it.

Keywords: decision management, decision management software, decision support, analytics, prescriptive analytics, IS curriculum.

1. INTRODUCTION

In the broadest sense, the terms Information Systems (IS) or Management Information Systems (MIS) refer to a wide range of computing applications and activities. In Academia, these terms refer to undergraduate degree programs that prepare students to meet the computer technology needs of business organizations, both public and private. In this paper, we will use IS to reflect these and other similar terms. This paper focuses on USA-based IS programs and the reader should assume that all discussions and research results are for USA-based programs.

Most IS departments or areas are located in business schools. IS programs develop knowledge and skill competency areas that students must master in order to effectively create and manage IS applications. Leidig and Salmela (2022) outline a competency framework for developing IS curriculums that include six major competency areas with each area having a set of sub-competencies. We contend that this competency framework leaves out a key competency area. This missing competency area is also not covered in IS research.

Academic programs must develop student competencies that are relevant to the students they teach and the businesses they prepare students to work in. One of the best ways to ensure relevancy is to monitor what is happening in IS practice world. Monitoring is difficult for academics to do. However, there are intermediaries that do the monitoring for academics. The two most notable are Gartner (https://www.gartner.com/en) and Forrester (https://www.forrester.com/bold). For example, Gartner develops actionable insights for their

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clients using rigorous research methodologies to study IS practice to ensure these insights are independent and objective.

Gartner has done a great deal of research on the missing IS competency, Decision Management (DM). Two quotes from Gartner highlight the importance of DM (Bolding added):

> "**Decision management is a discipline, not just a type of software.** It encompasses design principles, algorithms, best practices, vendors, products, books, professional societies, notation conventions and industry standards (such as Decision Model Notation [DMN])." (Schulte & Brethenoux, 2018, p.3).

> **"Pursue Decision Management as a discipline comparable to Data Management and BPM."** (Schulte & Brethenoux, 2018, p.3).

The primary outcome of this paper is to demonstrate the importance of DM and provide evidence that most top IS programs do not fully address the DM competency. In four phases, this paper argues that IS programs can do much more to prepare students to use DM. The first phase, "What is DM?" is for readers who have limited DM knowledge. The second phase documents the importance of DM by explaining how it supports the organizational decision-making process.

The third phase discusses the design and results from an exploratory research study. The study used the Observe, Orient, Decide, and Act (OODA) decision-making framework to analyze what IS programs are doing in the DM area. The study collected course data from IS programs in 23 universities listed as top IS programs in the U.S. News Best Colleges rankings ("Best Undergraduate Business Management Information Systems Programs," 2021, 2022). Each course was coded for course type, how the course content fit in the OODA framework, and whether it was a required or elective course.

The final phase of the paper summarizes the importance of DM and addresses how a comprehensive DM competency can be implemented in IS programs.

2. WHAT IS DECISION MANAGEMENT (DM)

When IS practitioners use the term DM, they are referring to a computing discipline that has three components:

1. **Methodology**: Process used to develop a model.
2. **Decision Model**: A representation, usually visual, of a decision situation.
3. **Decision Management System (DMS):** Technology Platform for implementing and processing the model.

Most readers will be familiar with Data Management which has a process for developing a data model such as the Relational model. Examples of technology platforms, Data Base Management Systems (DBMS), are Oracle Database and MySQL. Decision Management is similar in that there is a methodology used to develop a decision model. A decision model example is The Decision Model (TDM) which models a collection of decisions and the rules used to make the decisions (Goldberg & Segal, 2021). The major DMS that has implemented TDM is Sapiens Decision (https://sapiensdecision.com/).

DBMS and DMS differ in the functions they provide. The major functions of a Relational DBMS are managing a database: update and retrieval of data, and creation, design and maintenance of the relational data model. A TDM DMS implements the decision model and supports the processes of creating, analyzing, managing, and executing business decisions captured in the decision models. While they have different functions, both DBMS and DMS have the same components: methodology, model and technology platform.

Before looking at DM in more depth, it is important to understand the context and history of rule-based systems. The 1980s gave rise to the domain specific rule-based expert systems. These evolved in the 1990s into the more general Business Rule Management Systems (BRMS). BRMS are very beneficial for supporting certain categories of business decision making. However, BRMS have exhibited some major shortcomings such as their highly technical nature, only understandable by IT professionals, poor handling of complexity, lacking standardization and a decision construct/model. Thus, a BRMS is just dealing with a large collection of rules. These shortcomings led to limited adoption of BRMS over the years. The latest evolution is the replacement of BRMS with DMS technology.

The DM discipline is relatively new, starting around 2009 with the published book, The Decision Model (Von Halle and Goldberg, 2009) and the first real DMS, Sapiens Decision in 2011. DM is centered on business decisions rather than on the rules that enable them. The DM decision model provides a universal representation/model

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for all business and technical people. This helps close the communication gap between business and technical staff. This leads to stronger business involvement that can be entirely business-driven. One of the basic assumptions of DM is that decisions and decision logic belong to and should be managed by business people. A decision model and DMS software were needed to facilitate these changes.

Decision Model Example

As noted, The Decision Model (TDM) was one of the first decision models created and its major DMS implementation is Sapiens Decision. TDM is a way of representing business logic/rules that are platform and technology independent. The graphical TDM

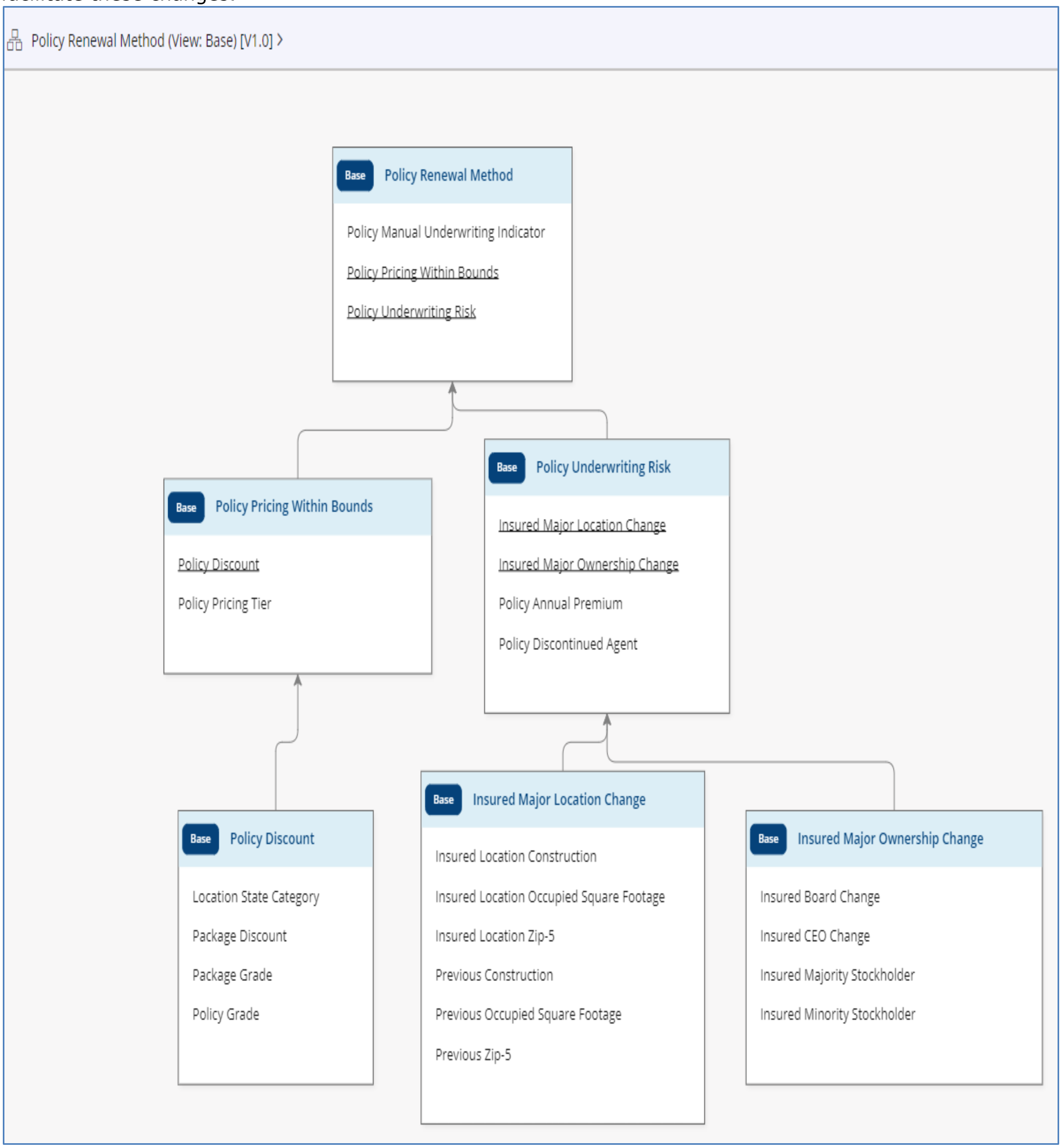

Figure 1a: TDM Graphical Model that Displays Collection of Decisions

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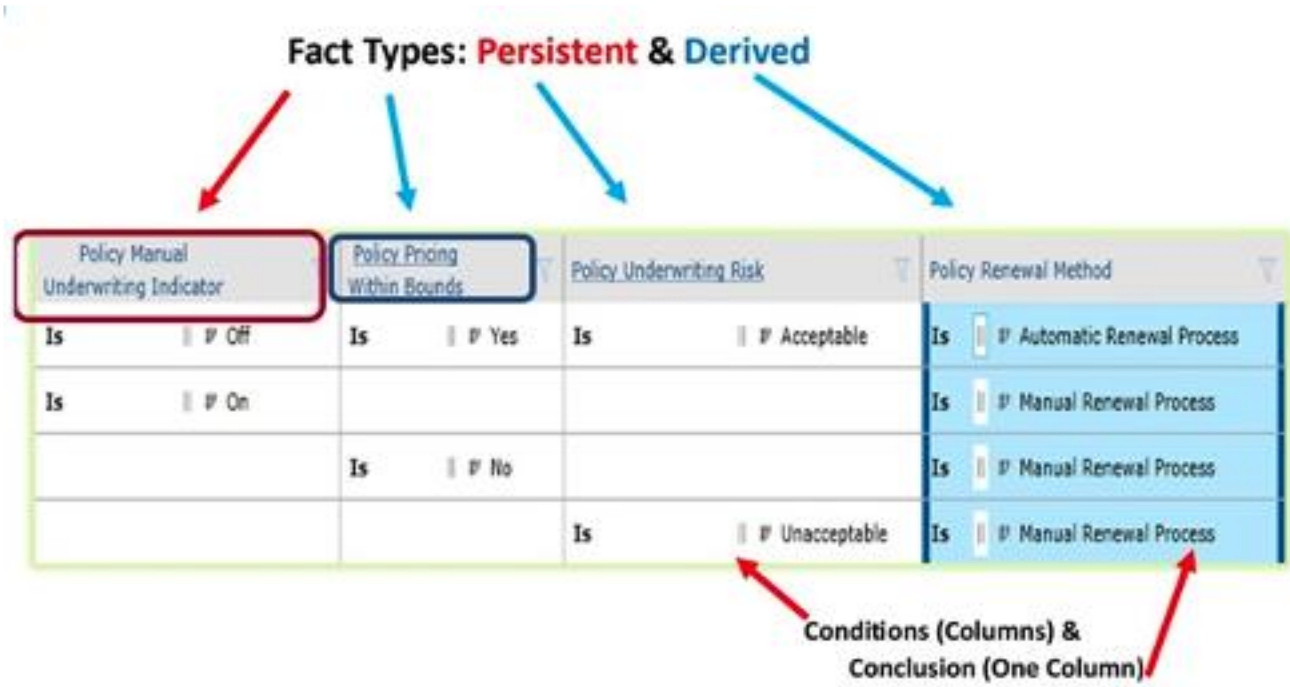

Figure 1b: Sample Decision Table from the Figure 1a Decision Model

model is shown in Figure 1a. Each of the boxes represents a decision. The major decision being modeled, root node of the model, is to recommend the policy renewal method for an insurance policy.

To understand the model, the reader needs some new terms used by people who work with rules.

- **Fact Type:** is a general classification or name of a fact, a name that names a piece of data/information.
- **Persistent Fact types:** data items that are inputs to the model, they exist permanently somewhere else, such as a database.
- **Derived Fact Types:** these data items take on a value when the model is executed.

Each of the names in Figure 1a are fact types. Those in blue and ones with underlined names are derived fact types. All the rest of the fact types are persistent data which are inputs to the model. Each of the decision boxes in the Figure 1a represents a decision table which contains multiple rows of conditions and conclusions. In each decision box, there is only one conclusion fact type. The fact types listed in blue are derived conclusion fact types and the ones in white part of a box are conditions fact types.

Figure 1a's root node decision table, Policy Renewal Method specifies that the decision table has sets of rules with three "condition" fact types and 1 "conclusion" fact type. The decision table is shown in Figure 1b. The column headings in the table are the fact types and the rows represent business rules. In TDM, all conditions are "and" together to test the rule. For example, the rule for row 1 would read: If Policy Manual Underwriting Indicator is "off" and Policy Pricing Within Bounds is "Yes" and Policy Underwriting Risk is "Acceptable", then Policy Renewal Method is "Automatic Renewal". Row 4's rule states: If Policy Underwriting Risk is "Unacceptable", then Policy Renewal Method is "Manual Renewal".

The simplest Decision Model would have a single decision table. The Decision Model in Figure 1a shows inferential links between decision tables. These links point to decision tables that will provide the derived values for the underlined fact type conditions in the father decision table. For example, Figure 1b shows two underlined fact type conditions: Policy Manual Underwriting Risk and Policy Pricing Within Bounds. Policy Pricing Within Bounds is derived when there is a match for a rule in the decision table that has two conditions, Policy Discount and Policy Pricing Tier. The value derived for Policy Pricing Within Bounds would then be used in the linked data table, Policy Renewal Method, to fire a rule. To go further down this path, Policy Discount is a derived fact type and the value would be set by firing a rule in the Policy Discount decision table.

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Thus, when we test and execute the Model in Figure 1a, the two paths in the model would be executed to come up with values for the two derived items in the decision table shown in Figure 1b. Policy Underwriting Indicator is an input to the model, thus, once the derived items have values, the system can check for rule matches and the value in the rule selected becomes the chosen Policy Renewal Method value. The derived fact types values would be the outputs of the model execution.

The DMS software would provide the model developer (Business or IS person) with:

1. tools that allow them to build the type of model shown in Figure 1a;
2. tools to develop all of the decision tables in the Figure 1a model; and
3. additional tools for maintenance of a fact type glossary, change management, logic validation, testing and deployment, execution, and governance and control.

2. DECISION MODEL NOTATION: DMN INTERNATIONAL STANDARD

The evolving area of business rules systems has developed a standard that is the culmination of 30 years of industry experience. DMN is an international standard decision modeling language and notation for the precise specification of business decisions and rules (*OMG Standards Group,* 2015). The first version of DMN was published in 2015, the current public version is 1.4, meantime, version 1.5 is complete and work has begun on version 1.6.

DMN implementations provide a business-friendly visual and model-driven approach to modeling decisions and rules using decision tables and a standard expression language. DMN decision models are rigorous enough to support execution directly with no technical support and can serve as human-readable documentation. DMN models are easy to read and develop by those involved in DM including business users, business analysts and technical developers. Having an international standard that guides the development of any DMS, highlights the importance of Decision Management.

The TDM model illustrated in the previous section is a special DMN implementation, implemented in Sapiens Decision DMS. It supports the development of a 3rd normal form decision model to maintain a simple and very business friendly DMN implementation. The DMN specification does not include a 3rd normal form model but it provides technical tools that you could implement it. Thus, Sapiens Decision DMN implementation does not include all the specs outlined in DMN. For example, it does not support multiple decision table formats and processing options and does not have an expression language. The TDM model, shown in Figures 1a and 1b, can be viewed as one type of DMN implementation.

One of the major benefits of a standard is vendor interchange, one vendor's DMN implementation can be easily set-up to run on another vendor's implementation. A list of best DMN implementations is at ("Best Decision Model and Notation (DMN) Software", 2023). The most up-to-date DMN texts are Taylor and Purchase (2023) and Silver (2018). A good introduction to DMN is found in Ronen (2022).

4. DECISION MANAGEMENT ROLES IN CHANGING PROGRAMMING PARADIGMS

To meet the demand for digital automation over the last 40 years, computer applications have become larger and more complex. The architecture in these programs required the deployment and maintenance of a single monolithic application. The monolithic architecture has given way to the service architecture. Software applications are viewed as suites/collections of independently deployable services. If not familiar with service architectures, read Appendix A, Service Architectures.

In this new service paradigm, DMS plays a critical role in creating services, a service provider, and providing orchestration tools via low/no code development tools. In DMS, any decision model can be deployed as a service and used by an application through standard service protocols REST and SOAP. For example, the decision model in Figure 1a can be deployed as a service. The user would have to supply values for all input/persistent fact types, provide fact types names which define where to put output/derived values, and a URL to locate the service on the Internet.

The problem today is that business decisions are buried in application code. Decision Management, especially DMS software, is helping to create a future in which business decisions are external to the application available for use by different application orchestration engines as compared to being buried in application code. DMS software allows decisions and decision services to be stored in a DMS repository.

A current example of what is happening in the practice is Allstate Insurance Company (Lenahan,

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2020, 2023). Allstate is in the process of separating decisions embedded in current application software. Allstate expects to gain adaptability, share to multiple applications, increased speed to market, and reduced cost and improved quality. They are using Sapiens DMS to create, store, deploy and execute these new decision models. Sapiens provides software help with this type of conversion in their Automated Logic Extraction (ALE) tool ("Announcing Automated Logic Extraction (ALE)," 2022). They suggest that this tool will reduce legacy system transformation costs by 50%. The tool transforms code to standard decision model format.

The bottom line is that the discipline of Decision Management is critical to the evolving program paradigms based on service architectures. Many DMSs also provide a no/low code platform for developing applications that execute decisions and offer external services. Like it did for Allstate, DMS facilitates an approach that implements the basic assumption of DM, which is decision logic and rules are a business asset worth managing independently of business process and data. DMS also provide a means for implementing another DM assumption, that decisions and decision logic belong to and should be managed by business people.

5. DECISION MANAGEMENT FROM A DECISION-MAKING PERSPECTIVE

The previous sections discuss the importance of DM. In this section, this theme will be continued by applying DM to one of the most important aspects of organizations, decision making. An organization must have a decision-making framework. One such framework used a lot in organizations is the OODA Loop model developed by US Air Force Colonel John Boyd in the mid-20th century (see Figure 2). Developed to train soldiers, the model is now applied to a variety of fields (Lewis, 2023).

The OODA loop is one way of thinking about the decision-making process. Broken down, the OODA loop stands for four distinct yet interrelated smaller loops: observe, orient, decide, and act. The OODA loop encourages decision-makers to think critically with the guiding outcome of continuously improving their decision cycles. In IS practice, the focus is on the models and technologies that apply to the decision-making process. The relevant models that are implemented in technology are shown in Figure 2, highlighting where the models are applied in the OODA model.

Multiple IS professionals are involved in each of these stages: data and application architects, business analysts, process modelers, etc. These professionals are usually well-versed in data, analytics, and process models but are not familiar with decision models (Schulte & Hamer, 2019). Some of them regard rule-based systems as obsolete. However, DM using Decision Management Systems (DMS) rule-based systems is changing this view. IS professionals can specialize in certain area(s) but they need to have a good understanding of model usefulness in the four areas. IS teams working on improving a decision-making process need be formed with model and technical knowledge in all four areas (Taylor, 2016).

Figure 3 breaks down the four types of analytics models and technologies and how they are applied to the four different phases. For example, organizations use descriptive, diagnostic and predictive analytics to support people making decisions; these skills and knowledge are usually taught in business intelligence courses. Figure 3 shows how people play a major role in these activities.

Decision Management (DM) is starting to play a major role in decision support and automation in the Decide phase of OODA model. This paper has focused on rule-based DM. Those in IS who are aware of this area would have this view. In the last few years, a broader definition of DM has emerged based on changes in IS practice. Schulte and Hamer (2019) clearly summarize the emerging DM perspective. The three disciplines that contribute to better DM are Machine Learning, Optimization, and Business Rules. Different professionals will be involved in the different activities in the DM and they need to have a basic understanding of each of these disciplines and how the three disciplines interact (Taylor, 2016).

These disciplines all focus on the question "What can we make happen?" Thus, people sometimes refer to this area as Prescriptive Analytics. IS practice must move away from the rule-based DM perspective to the more encompassing view that the term DM includes any discipline that supports the "Decide" phase. Figure 3 shows DMS as one example of the technology used because rule-based systems is the focus of this paper, machine learning or an optimization tool would be other technologies that could be used.

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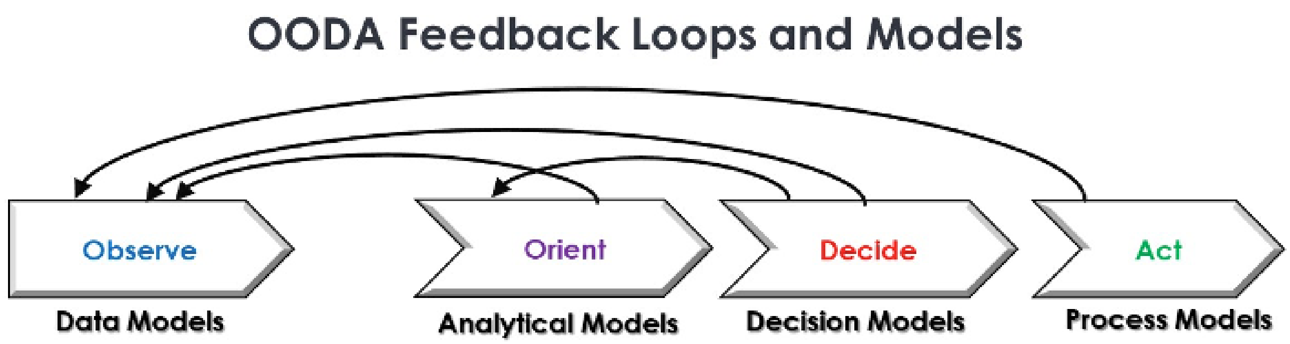

1. Data from multiple sources about the situation (input variables) are collected during the **observation** phase. This is where **data models** help.
2. Data is put into context -filtered, analyzed, and enriched- and its implications are considered in the **orientation** phase. This is where **analytical models** apply.
3. Determination of what to do is made in the decision phase, actionable insights discovered to determine the best available response. This is the **heart of decision management**, and where **decision models** can be used. Prescriptive Analytics can also be used, such as AI (Machine Learning, Natural Language Processing…) and Optimization (Linear Programming) techniques, with decision models or as stand-alone models.
4. The response is executed in the **action** phase. This is where **business process models** may be used to specify the sequence of activities that are triggered by the decision.

Figure 2 (Modified; Source: Schuite and Brethenoux, 2018, p. 5 and 6)

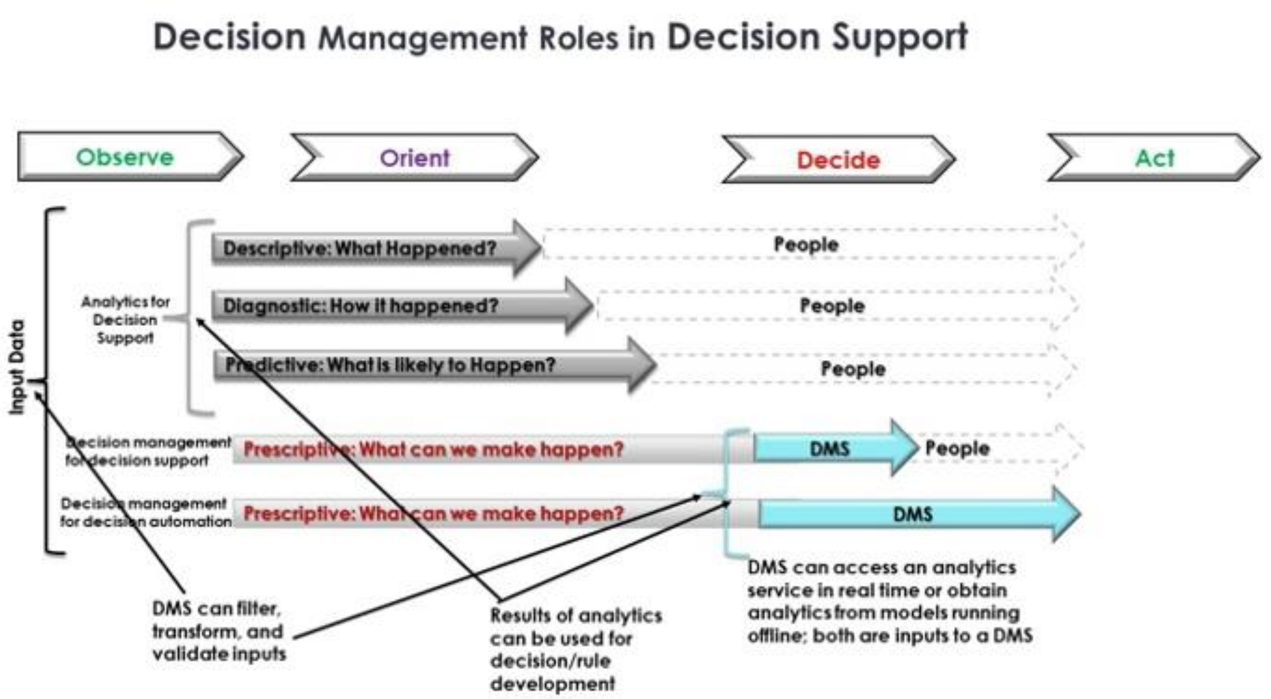

Figure 3 (Modified; Source: Schulte and Brethenoux, 2018, p.8)

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Popa (2022) adds two more areas to the three core disciplines, Natural Language Processing (NLP) and Graph Techniques, and reports on a 2021 Gartner Survey of approximately 700 participants who are using or planning to use these methods. The results are shown in Table 1.

Technology	Machine Learning	Optimization	Rules-Based	NLP	Graphs
In use	36%	32%	31%	32%	30%
Install within 5 years	62%	64%	62%	60%	60%
Total %	98%	96%	93%	92%	90%

Table 1: 2021 Gartner Survey Results (Popa, 2022)

All organizations expect to have at least 90% adoption within five years. Machine Learning and Optimization have the highest adoption rates and expected adoption rates. Rule-Based Systems (DMS) ranked third, highlighting the importance of these systems and providing support for the argument presented in this article. The overall results make clear how important these technologies are to future IS projects.

Figure 3 also shows the three areas where DMS can support the decision-making process. Although not intended, data validation has become a critical DMS application in many organizations. DMS can filter, transform, and validate inputs wherever inputs enter the process, especially in the observation and decide phases. Analytic results can be used for decision and rule development. DMS can also access any analytics or other service in real time or obtain them from off-line applications. Both validated data and analytics are inputs to a decision model. Both of these illustrate how DMS can orchestrate all of the services or inputs in the Decide phase.

6. AN EXPLORATORY RESEARCH

To study the coverage of DM knowledge in IS programs, we selected programs representative of top IS programs in the US using the U.S. News & World Report publications ("Best Undergraduate Business Management Information Systems Programs," 2021, 2022). We verified the curricula of these programs against the most recent IS program guidelines (Leidig & Salmela, 2022), leaving 23 programs coming from a mix of mostly large public universities and a few private colleges. All were IS major programs in a business or management school. We collected course descriptions and course syllabi, if available, from the programs websites and used the information to map the courses to the OODA framework discussed above (see Figure 2). The goal was to look at how each phase of the decision-making process was populated with courses. The data collection and research findings are reported in the remainder of this section.

Data Collection and Coding

The courses selected for coding needed to provide support for one of the phases in the OODA decision-making framework. Placement of courses in the framework was discussed in the previous section, (see Figures 3 and 4). Each course was coded as either a required or elective course. Prescriptive Analytics courses were also coded for the decision modeling methods taught in the course. For detailed discussion of data collection and coding results, see Appendix.

Course Coverage in Each Phase of OODA

We mapped 148 courses from the 23 IS programs to the OODA framework. Table 2 and 3 show the numbers and percentages for each OODA phase. For example, the first row of Table 2 shows that thirty-five courses (23.6% of all the courses) were in the Observe phase, an average of 1.52 courses per program and that all 23 programs (100% of the programs) had course coverage in the Observe phase. The results show that the top IS programs' courses focus primarily on the front-end of the OODA framework: Observe and Orient, course coverage by 100% and 96% of all programs, where the dominant disciplines are data management (35 courses) and analytics (76 courses); while the back-end of the model, Decide and Act, where the dominant disciplines are prescriptive analytics (26 courses) and BPM (11 courses), is covered by fewer programs (70% and 35% of total programs, respectively).

OODA Phase	Number Of Courses	% Of Total Number of Courses	Average Number of Courses per Program	Number of Programs with Course	% Of Total Programs
Observe	35	23.6%	1.52	23	100%
Orient	76	51.4%	3.30	22	96%
Decide	26	17.6%	1.13	16	70%
Act	11	7.4%	0.48	8	35%
Total	148	100.0%			

Table 2: Course Count and Percentage by OODA Phases

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OODA Phase	Program Requirement	Number of Courses	% Of Total Number of Courses	Average Number of Courses per Program	Number of Programs with Course	% Of Total Programs
Observe	Required	21	14.2%	0.91	21	91.3%
	Elective	14	9.5%	0.61	8	34.8%
Orient	Required	27	18.2%	1.17	16	69.6%
	Elective	49	33.1%	2.13	20	87.0%
Decide	Required	11	7.4%	0.48	9	39.1%
	Elective	15	10.1%	0.65	12	52.2%
Act	Required	2	1.4%	0.09	2	8.7%
	Elective	9	6.1%	0.39	7	30.4%
Total		148				

Table 3: Program Requirement by OODA Phases

Table 3 specifies whether courses were required or elective. For example, there were 21 required courses and 14 electives in the Observe phase, and only 2 required and 9 electives in the Act phase. The results show the preference for required front-end courses in the Observe and Orient phases. In the Observe phase, all programs but two (91.3%) had a required course, in the Orient phase, 16 out of 23 programs (69.6%) had a required course. In contrast, only 39.1% programs required a Decide course and 8.7% required an Act course. In addition, Observe and Orient phases had a large number of electives. Given that these phases had most required courses and large number of electives, the results highlight that these programs put more importance on Observe and Orient phases, more importance on data management and descriptive, diagnostic and predictive analytics courses.

Coverage of DM Knowledge in IS Programs

The goals of this paper were to demonstrate the importance of Decision Management (DM) and provide evidence that most top IS programs do not fully address the DM competency. The paper defined DM the way it is currently used in IS practice as a computing discipline that has three components: Methodology (process used to develop a model); Decision Model, and Decision Management System (DMS). We broaden the DM definition in the previous section to reflect the change in IS practice to move to a more encompassing view that includes any discipline that supports the "Decide" phase. The three main disciplines in this view are Rule-base (RS), Machine Learning (ML), and Optimization (OP). All three disciplines will have a process to develop a decision model and technology to implement the decision model. Earlier sections of the paper presented the Rule-based view.

While most programs offer courses in the Observe and Orient phases (100% and 96%, respectively), fewer programs offer courses in the Decide phase (70%) and only 39.1% required a Decide course and most of those courses were electives. These results point out that the Decide phase receives less attention than the Observe and Orient phases.

We coded courses in the Decide phase using our broadened DM definition where the primary decision methods are RS, ML, and OP. We added a general analytics method (AN) for methods that did not fit in the three primary methods and a combined code for courses that use multiple methods. All AI courses are machine-learning based. We also looked at all Operation Research courses and we coded those that were optimization based. The results are shown in Tables 4 and 5.

Of the 26 Decide courses, only 1 included Rule-based decision management (RS) content, which accounted for 3.8% of all the Decide courses. The RS content was taught in three classes in a required BPM course, providing an overview of Rule-based systems. Conversely, the traditional OP methods were in 46.2% of the courses, ML in 30.8%, and ML, OP, and ML-OP combined were in 80.8% of all the Decide courses.

From the perspective of program requirements, 8.7% of the programs required a course teaching ML, and 26.1% of the programs offered ML electives; 21.7% of the programs required a course teaching OP, and 21.7% offered OP electives; 8.7% of the programs required a course teaching general AN methods, and 8.7% offered AN electives.

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Decision Modeling Methods	Number Of Courses	Average Number of Courses per Program	% Of Decide Phase Courses	Number of Programs with Course	% Of Total Programs
ML	8	0.35	30.8%	8	34.8%
OP	12	0.52	46.2%	10	43.5%
ML-OP	1	0.04	3.8%	1	4.3%
RS	1	0.04	3.8%	1	4.3%
AN	4	0.17	15.4%	4	17.4%
Total	26	1.13	100.0%		

Table 4: Decision Modeling Methods Taught in Prescriptive Analytics Courses

Decision Modeling Methods	Program Requirement	Number of Courses	% Of Decide Phase Courses	Average Number of Courses per Program	Number of Programs with Course	% Of Total Programs
ML	Required	2	7.7%	0.09	2	8.7%
ML	Elective	6	23.1%	0.26	6	26.1%
OP	Required	6	23.1%	0.26	5	21.7%
OP	Elective	6	23.1%	0.26	5	21.7%
ML-OP	Elective	1	3.8%	0.04	1	4.3%
RS	Required	1	3.8%	0.04	1	4.3%
AN	Required	2	7.7%	0.09	2	8.7%
AN	Elective	2	7.7%	0.09	2	8.7%
Total		26				

Table 5: Program Requirement by Decision Modeling Methods

The results provide evidence to support the argument put forth in this paper that most top IS programs do not fully address the DM competency in general and for rule-based systems specifically. The rule-based method was only offered as a small part of a required BPM course.

It is surprising to see few offerings in Machine Learning given the strong need for AI-based knowledge. On the flip side, the OP findings were more than expected in terms of most courses and most required courses and the largest number of programs with a course. This may reflect that some IS programs are associated with Operations Research or Management Science programs. The bottom line is that IS programs are not doing a very good job dealing with decision support in the Decide phase of the decision-making process, especially rule-based DM.

7. CONCLUSION

The evidence of the research reported in this paper clearly indicates that all but one top IS program does not fully address the Decision Management (DM) competency. Even the 1 program provides only minimal content on rule-based DM. The paper sections before the research section demonstrated that Rule-based DM and the DMS software is important because it:

- Allows companies to manage decisions and rules independently in a respiratory, separated from the applications that execute the decisions.
- Is critical to the evolving programming paradigms that view programs as collections of services. Decision Services, which execute decisions, will be a key component in developing composite software systems that include a DMS that provides a low code development and

execution platform.
- Allows business people to be more involved in model building, execution and making changes in the decisions. Staff who know the organization's "business" play key roles and they can better communicate with technical experts because decision models are easily understood by both groups.
- Has an evolving International Standard, DMN, to guide DMS software development.
- Leads to better business outcomes such as adaptability (more change happens in business decisions-rules), speed to market, cost reduction, improvement in quality, etc.
- Can play a key role in the decision-making process. DMS decision models can be used to validate data and integrate or orchestrate services as inputs, including decision services such as machine learning and optimization software services.

Moreover, IS practice surveys (Popa, 2022) have shown, that within the next five years, organizational adoption rates for DM technologies within the top three disciplines will be: Machine Learning (ML), 98%; Optimization (OP), 96%; Rule-base systems (RS), 93%. These adoption rates allow for a more expansive definition of DM, namely that it includes any discipline that supports the Decide phase of decision-making. ML has an AI base and OP has an Operations Research base. However, the Rule-based (RS) discipline has no clear home. **Thus, it is proposed that IS programs should be the home base for RS.**

IS programs can implement this comprehensive DM competency by focusing on offering courses with the rule-based DMS content discussed in this paper. Three options are possible:

1. Offer a rule-based DMS course. The best reference textbooks: Von Halle, B., & Goldberg, L., 2009; Silver, 2018; and Taylor & Purchase, 2023.
2. Offer an integrated course with two disciplines. The study found one program with an ML-OP course and another with BPM-RS. Given what is happening in IS practice, the best integration for rule-based DMS would be ML-RS, because they are often used together in IS practice. For a place to just overview RS discipline, the BPM-RS works.
3. A program may want to just overview all three disciplines and show how they can be used together by creating a ML-OP-RS course.

8. ADVICE TO IS PROGRAM DIRECTORS

With the current rapid adoption and expected future adoption of new technologies to facilitate DM, IS programs should significantly increase DM content in their programs related to the three disciplines especially Rule-based DMS. ML and OP courses are probably available in other areas but may need to be tweaked to fit specific needs or taught inside the IS program. Our research results showed that most ML courses were developed and taught inside the IS program. Gartner's advice to "Pursue Decision Management as a discipline comparable to Data Management and BPM" needs to be acted on as soon as possible. How is your IS program going to get started on implementing DM?

9. REFERENCES

"Announcing Automated Logic Extraction (ALE)." (2022). Retrieved from https://sapiensdecision.com/news-events/announcing-automated-logic-extraction-ale

"Best Decision Model and Notation (DMN) Software." (2023). *SourceForge Software Directory*. Retrieved from https://sourceforge.net/software/decision-model-and-notation-dmn

"Best Undergraduate Business Management Information Systems Programs." (2021). *U.S. News & World Report.* Retrieved from https://www.usnews.com/best-co

"Best Undergraduate Business Management Information Systems Programs." (2022). *U.S. News & World Report.* Retrieved from https://www.usnews.com/best-co

Goldberg, L., & Segal, G. (2021). A primer on the decision model. Retrieved from https://sapiensdecision.com/wpcontent/uploads/2021/12/A-Primer-on-The-Decision-Model-2021-12 15.pdf

Leidig, P. M., & Salmela, H. (2022). The ACM/AIS IS2020 competency model for undergraduate programs in information systems: A joint ACM/AIS task force report. *Communications of the Association for Information Systems*, 50, n/a. doi:10.17705/1CAIS.05021

Lenahan, T. (2020). Achieving business agility in an industry under transformation. *Sapiens*

ISSN: 2473-4901
v9 n6023

Conference Presentation. October 2020. https://www.youtube.com/watch?v=tNg7Qm79hC4

Lenahan, T. (2023). Thrilling customers, one decision at a time. doi:https://video.sapiens.com/watch/h3qLPDQz3vwzHp8KHkXPnY?utm_medium=email&_hsmi=74642183&_hsenc=p2ANqtz-8slmQQgSXV7QANaoxeUtRKzfPduvEAA7DSch4oF0sFd3JCAbmsM5rVvla2BRcYBV0ykREPggPNFvkkD73Hrv-H7p6w4g&utm_content=74642183&utm_source=hs_automation

Lewis, S. (2023). Definition: OODA loop. *TechTarget Editorial*, Retrieved from https://www.techtarget.com/searchcio/definition/OODA-loop#:~:text=The%20OODA%20loop%20(Observe%2C%20Orient,as%20more%20data%20becomes%20available

Popa, A. (2022). Combine predictive and prescriptive analytics for better decision making. *Gartner Research.* doi: G00775795

OMG Standards Group (2015). Precise Specification of Business Decisions and Business Rules. Retrieved from https://www.omg.org/dmn

Ronen, G. (2022). From business rules to decision management using DMN. Retrieved from https://www.trisotech.com/from-business-rules-to-decision-management-using-dmn/

Schulte, R., & Brethenoux, E. (2018). How companies succeed at decision management. *Gartner Research.* doi: G00341368

Schulte, R., Brethenoux, E., & Miers, D. (2019). Develop good decision models to succeed at decision management. *Gartner Research.* doi: G00341367

Schulte, W. R., & Hamer, P. D. (2019). How to use machine learning, business rules and optimization in decision management. *Gartner Research.* doi: G00389774

Silver, B. (2018). DMN Method and Style: A Business Practitioner's Guide to Decision Modeling, 2nd Edition. Cody-Cassidy Press.

Taylor, J. (December, 2016). Bringing clarity to data science projects with decision modeling: A case study. *Decision Management Solutions*.

Taylor, J., & Purchase, J. (2023). Real-world decision modeling with DMN (2nd ed.). JTonEDM.

Vashisth, S., Schulte, R., & Vincent, P. (2019). Innovation tech insight for decision management. *Gartner Research*. doi: G00433988

Von Halle, B., & Goldberg, L. (2009). The decision model: A business logic framework linking business and technology. Auerbach Publications.

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APPENDIX A
Service Architectures

To meet the demand for digital automation over the last 40 years, computer applications have become larger and more complex. The architecture in these programs required the deployment and maintenance of a single monolithic application. The monolithic architecture gave way to the service architecture. Software applications are viewed as suites/collections of independently deployable services.

A service is a basic software building block program in any language, that is a black box to the user (encapsulated). To use or consume the service, the user application needs to provide inputs, receive outputs, and know the method for triggering the service, usually from a URL. Assuming a collection of services, a key question is "How do we know which services to execute when?” The answer is that a computer application provides the orchestration engine which specifies which services to execute when.

The service architecture has simplified the building and maintenance of programs. The simplification is to extract and standardize common computing tasks from the body of application programming source code and turn them into services. The first change was to replace custom data management tasks in programs with Data Base Management Systems (DBMS). The next big change replaced the step-by-step embedded procedure logic in programs with Business Process Management Systems (BPMS). Thus, a BPMS application becomes the orchestration engine to execute a set of services. Next came the separation of business rules from source code creating a collection of business rules that is managed by Business Rule Management Systems (BRMS). A BRMS provides a set of services, used mainly by technical professionals, to create and manage a collection of rules. The latest evolution is the replacement of BRMS with Decision Management Systems (DMS).

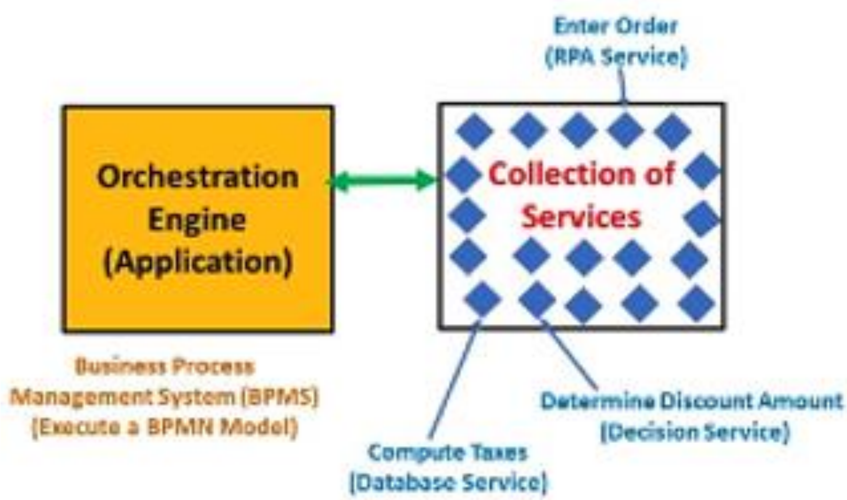

Figure 5: Composite Application Development

Figure 5 shows how an application/program is a collection of services. There is an application which is an Orchestration Engine for a collection of services that the application is using. Listed in Figure 5 are some Orchestration Engine examples such as BPMS or Java. All low code development platforms implement this service perspective where the building blocks in the model components are used to create an application using internal and/or external services. This programming approach is often referred to as composite application development because model components and services are used to build a program instead of writing code.

Many DMSs include an Orchestration Engine or are integrated with one. For example, Sapiens Decision provides a Flow feature that creates a decision process flow for executing different decision models and provides access to external services if needed. Trisotech DMS is integrated into its digital automation suite with a Workflow Automation tool and a Case Automation tool, which serve as Orchestration Engines for DMN services created in the Decision Automation tool.

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The business models of the future will be built on the applications of the future. And the applications of the future will be built on services. They service architectures allow you to upgrade and update individual capabilities within your application architecture. You can pick and choose the best of each service to create an application that is greater than the sum of its parts.

APPENDIX B
Data Collection and Coding

Our units of analysis were Information Systems (IS) programs and courses. When coding programs and courses, the program descriptions and course descriptions on university web sites were used as content sources. All coding of the programs and courses was conducted by both researchers independently for cross-referencing. Where conflicts existed, the differences were discussed until consensus was reached.

A program is considered an IS program if its curriculum complies with the IS curriculum guidelines that include six competency areas: (1) Foundations of Information Systems, (2) Data and Information Management, (3) Technology (IT Infrastructure and Secure Computing), (4) Development (System Analysis & Design and Application Development), (5) Organizational Domain (ethics, Use and Implications for Society and IS Management & Strategy), and (6) Integration (IS Project Management and IS Practicum) (Leidig & Salmela, 2022). If after going through program course descriptions, the program was coded as an IS program if all competency areas were represented in the course descriptions. The programs that did not meet the criteria for being IS program were labeled Analytics programs because they contained courses that were predominantly analytics courses. The Analytics programs were usually missing competency areas 1, 3, and 4.

As IS programs are commonly located in business schools, we collected data from the best undergraduate business management information systems programs listed in the U.S. News & World Report (2021, 2022). If a program was listed in both years, the 2022 data was collected. If it was in one year only, we used data of the year it was listed. Only business school IS programs were included for comparability. We looked at 28 universities and found 34 programs including IS and Analytics courses. We included only IS major programs in the data analysis to maintain comparability. As a result, the dataset includes 23 IS major programs from 23 universities. U.S. News & World Report did not provide a clear definition of an IS program. The 11 programs that were not included in our analysis were Analytics programs. Given our definition of IS program, 5 Universities got dropped because they had no IS programs, just Analytics programs. Of the 5 dropped, two were ranked 1 and 2 in the U.S. News & World Report rankings.

Course Category and Definition

For these 23 programs, we collected courses relevant to the observe-orient-decide-act (OODA) decision making framework discussed earlier in this paper, see Figure 2. In the OODA framework, data are collected in the Observation phase, contextual analysis is done in the Orient phase using analytics, decision models are applied to determine what to do in the Decide phase, “what to do” specifies or triggers sequences of activities in business process models in the Act phase. The IS programs have the following courses relevant to the OODA framework: Data Management courses fit in the Observe phase; Descriptive, Diagnostic, and Predictive Analytics courses fit in the Orient phase; Prescriptive Analytics courses utilizing decision modeling, support, and automation fit in the Decide phase; and Business Process Management (BPM) courses fit in the Act phase. The defining criterion for each course category is described in the Table 6 below. Courses were categorized based on information in the course description. When no official course description was found, we used information found about the course on the university’s website.

OODA Phase	Course Category	Defining Criterion
Observe	Data Management	Database technologies, data modeling, SQL, data curation, data management.
Orient	General Analytics	Where course description does not provide enough information to determine the specific type of analytics aforementioned.

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	Descriptive Analytics	Descriptive Analytics is the examination of data or content, usually manually performed, to answer the question "What happened?" (or What is happening?), characterized by traditional business intelligence (BI) and visualizations such as pie charts, bar charts, line graphs, tables, or generated narratives.
	Diagnostic Analytics	Diagnostic analytics is a form of advanced analytics that examines data or content to answer the question, "Why did it happen?" It is characterized by techniques such as drill-down, data discovery, data mining and correlations.
	Predictive Analytics	Predictive Analytics is a form of advanced analytics which examines data or content to answer the question "What is going to happen?" or more precisely, "What is likely to happen?", and is characterized by techniques such as regression analysis, forecasting, multivariate statistics, pattern matching, predictive modeling, and forecasting.
Decide	Prescriptive Analytics	Prescriptive Analytics is a form of advanced analytics which examines data or content to answer the question "What should be done?" or "What can we do to make ________ happen?", and is characterized by techniques such as machine learning, optimization, and rule-based systems.
Act	Business Process Management	Business process modeling, design and management

Table 6: Defining Criteria of Course Categories

Course Counts of Each Phase of the OODA Framework

We found 130 courses, 126 of them fit in one course category, and 4 courses fit in two categories and were included in each category it fit. Table 7 shows courses that fit in one category: there were 32 Data Management courses, 84 Analytics courses, and 10 BPM courses. Table 8 shows courses that fit in two categories: 3 courses fit in both Analytics and Data Management, and 1 course fit in both Analytics and BPM.

Single Course Category	Number of Courses
Data Management	32
Analytics	84
BPM	10
Total	126

Table 7: Number of Courses by Course Category – Single-Category Courses

Overlapping Course Category	Number of Courses
Data Management & Analytics	3
BPM & Analytics	1
Total	4

Table 8: Number of Courses by Course Category – Two-Category Courses

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Table 9 shows the number of courses in each phase of the OODA framework. Observe had 35 courses, Act had 11 courses. Descriptive, Diagnostic, and Predictive Analytics fit in the Orient phase of the OODA framework, and Prescriptive Analytics fit in the Decide phase. There were 26 courses that had Prescriptive Analytics content, so the Decide phase had 26 courses. As a course may include more than one type of analytics content (sub-categories of Analytics courses are explained in the next section), to count the number of courses in the Orient phase, we included the courses that cover any of Descriptive, Diagnostic, Predictive, or General Analytics but not Prescriptive Analytics. There were 76 courses in the Orient phase. Note the number of courses in each phase added to 148 because some courses fell in more than one category. The number 148 was used as the denominator in the course count percentage calculations of each OODA phase.

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OODA Phase	Course Type	Number of Courses
Observe	Data Management	35
Orient	Non-prescriptive Analytics (Descriptive, Diagnostic, Predictive, General Analytics but not Prescriptive Analytics)	76
Decide	Prescriptive Analytics	26
Act	BPM	11
Total		148

Table 9: Number of Courses by Phases of the OODA Framework

Sub-categories of Analytics

According to the course descriptions, an Analytics course could cover one or more types of Descriptive, Diagnostic, Predictive, or Prescriptive analytics. Therefore, the coding of an Analytics course could overlap two or more of these categories. If no specific information was available in the course description to help decide which category the course belonged to, the course was coded a General Analytics course. The numbers of courses of each sub-category are listed in Table 10.

Sub-Category of Analytics	Number of Courses
Descriptive Analytics	18
Diagnostic Analytics	26
Predictive Analytics	36
Prescriptive Analytics	26
General Analytics	23

Table 10: Number of Courses by Sub-Category of Analytics

Prescriptive Analytics Modeling Methods

Prescriptive Analytics courses covered different decision modeling methods including Optimization (OP), Machine Learning (ML), and Rule-based decision management systems (RS). Some courses covered both ML and OP. Some courses covered methods that did not fit in the three primary methods and were coded general analytics (AN). The decision methods categories and the number of courses in each category are listed in Table 11.

Decision Modeling Methods	Description	Number of Courses
ML	Artificial intelligence focus on machine learning	8
OP	Operations research that focuses on optimization methods	12
ML-OP	AI (machine Learning) & OR optimization methods	1
RS	Rule-based decision management	1
AN	Other general analytics techniques	4

Table 11: Number of Courses by Prescriptive Analytics Technique

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Course Role in Program

A course may be required for an academic program or an elective. For the 130 courses of the 23 programs in this study, 55 courses were required and 75 were electives. See Table 12.

Course-Program Requirement Code	Description	Number of Courses
Required	Required course for the program	55
Elective	An elective course for the program	75
Total		130

Table 12: Number of Courses by Program-Course Requirement