Managing portfolio interdependencies: The effects of visual data representations on project portfolio decision making

Catherine P Killen, University of Technology, Sydney, Australia
Faculty of Design, Architecture and Building
PO Box 123, Broadway NSW 2007, Australia
email: c.killen@uts.edu.au ph:+612 9514 8632

STRUCTURED ABSTRACT

Purpose

This study aims to improve decision quality, and therefore project and portfolio success, by testing the influence of different visual representations of interdependency data in a simulated decision experiment. A network mapping approach to visualize project interdependencies is introduced and compared with matrix and tabular displays.

Design/methodology/approach

A simulated decision task in a controlled classroom setting tested five hypotheses though a sample of 480 experiments.

Findings

The type of data representation used is associated with differing levels of decision quality, and the use of network mapping displays is aligned with the best results.

Research limitations/implications

The findings are limited as this experiment-based study presented a simplified decision scenario and involved students rather than practicing managers. The findings are best interpreted in combination with organization-based research.

Practical implications

The findings of this study suggest that visual data displays, particularly network mapping displays, can provide benefits and improve project portfolio decision quality. Managers may draw upon this study to design ways to include visual data representations in their PPM decision processes.

Originality/value

This study uses experimentation to complement organization-based studies to better understand the influence of different methods of visualizing data and managing interdependencies between projects. This research provides an important contribution to meet the acknowledged need for better tools to understand and manage project interdependencies.

Keywords: Project portfolio management; data visualization; network mapping; interdependencies; experiments; decision making

Article classification: Research Paper

Keywords: Project portfolio management; project interdependencies; portfolio interdependencies; data representations; visualization; network mapping; cognitive fit

INTRODUCTION

Decision making is central to an organization's management of its investments across a portfolio of projects through project portfolio management (PPM). PPM is of growing importance as a strategic decision-making capability in an increasingly complex project landscape (Levine, 2005, Cicmil et al., 2006, Jonas, 2010). However, interdependencies between projects can cause unpredictable interactions and reactions in the system in response to delays or changes in other projects (Aritua et al., 2009, Perminova et al., 2008, Collyer and Warren, 2009, Petit, 2012). It is widely accepted that organizations must be able to understand the dependencies between projects in their portfolio in order to make appropriate project decisions for the best portfolio outcomes (Verma and Sinha, 2002, Blau et al., 2004, Bathallath et al., 2016). This paper presents an exploratory research study that aims to improve project portfolio decision making, and therefore project and portfolio success, by testing the influence of different visual representations of interdependency data in a simulated decision experiment.

A project portfolio is a collection of projects managed under a common budget to achieve organizational aims. Resource allocation decisions, such as project selection and termination decisions, are central to the management of a project portfolio. Portfolio decisions are responsible for ensuring resource adequacy, dynamic agility, and strategic alignment using a portfolio-level rather than a project-level perspective (Floricel and Ibanescu, 2008, Petit, 2012). To best support long-term project portfolio performance, project portfolio decisions aim to take a holistic view that ensures balance across the portfolio and considers relationships between projects.

Multiple characteristics of proposed and ongoing projects must be considered in PPM decision making. By supporting decision makers with appropriate structures and portfolio-level information about projects and their interrelationships, PPM aims to improve the performance of the project portfolio as a whole. PPM decisions are made by managers (often in teams) and are therefore subject to limitations in human cognitive capability for analyzing a variety of information in limited time. PPM processes are designed to assist such decision making by providing a holistic view of the project portfolio, ensuring that data are available, and offering representation methods and tools to facilitate analysis of project data (Cooper et al., 2001, De Reyck et al., 2005, Kester et al., 2011). Information quality, allocation, and cooperation are key ingredients for effective project portfolio management (Jonas et al., 2013). Organizational success depends on appropriate PPM methods and tools that improve the quality of the information supporting these portfolio-level decisions.

The interdependencies between projects add to the complexity of PPM decision making and must be considered along with financial, strategic, risk, resource, and other factors. Portfolios of complex and interdependent projects are increasingly common and there is an identified need for better tools to understand and manage the relationships between projects. New processes, tools, and techniques are regularly proposed and evaluated in PPM literature and research (Archer and Ghasemzadeh, 1999, Dickinson et al., 2001, Dawidson, 2006, Kester et al., 2009). However, measuring the effect of a new tool or method is difficult because each organizational environment is different and there are many uncontrollable factors that influence project performance. While research in organizational settings can provide valuable insights, such settings do not provide a reliable and static environment where it is possible generalize findings. Simulated decision challenges in a controlled setting can complement organization-based research by experimentally testing the effects of changes in a systematic method.

This paper draws upon theories of bounded rationality and cognitive fit and explores alternative data representation methods for managing project interdependencies. Building on organizational trials of a new method for visualizing project portfolio interdependencies (Killen and Kjaer, 2012), the research reported in this paper employs controlled experimentation in a classroom setting to test the effect of three different data representation formats for displaying project interdependencies to support PPM decision making.

LITERATURE REVIEW

PPM decision making and project interdependencies

An organization's PPM capability involves decision makers in organizational activities that provide a holistic framework for the management of the project portfolio. The literature highlights that PPM is primarily a strategic decision-making process which involves identifying, minimizing and diversifying risk, identifying and responding to changes, and understanding, accepting and making trade-offs (see for example (Kester et al., 2011, Urhahn and Spieth, 2014)). PPM decisions require consideration of multiple factors and the ability to envision alternative future consequences of project decisions across a portfolio. Decision quality has a major influence on project portfolio success (Matheson and Menke, 1994).

Numerous PPM studies indicate that high-performing organizations use carefully compiled executive-level teams, often called portfolio review boards (PRB), to make portfolio decisions (see for example (Cooper et al., 2001, Dickinson et al., 2001, Lerch and Spieth, 2013, Killen et al., 2008)). The decision making requires a central view of all projects in the portfolio and the PRB is informed by methods that facilitate group decision making, including portfolio maps and other graphical and visual displays (De Maio et al., 1994, Cooper et al., 2001, Mikkola, 2001);

however, the maps must be carefully designed and customized for effective portfolio decision making (Phaal et al., 2006, Geraldi and Arlt, 2015). The use of such visual data representations is correlated with better portfolio performance (Cooper et al., 2001, Killen et al., 2008).

PPM decisions aim to consider the portfolio as a whole, but often treat each project as an isolated entity – such as in portfolio maps or ranking systems where each project is a singular entity, and no information is supplied on relationships between projects (Mikkola, 2001). However, projects are often interdependent, and the literature highlights a range of types of interdependencies, such as resource and technical dependencies, and dependencies based on learning and organizational structures (Jerbrant, 2013, Parker et al., 2015, Verma and Sinha, 2002, Eilat et al., 2006, Blau et al., 2004, Killen and Kjaer, 2012, Bathallath et al., 2016). Understanding these interdependencies is important because they can result in flow-on effects throughout the portfolio, stemming from decisions or problems related to individual projects (Aritua et al., 2009, Collyer and Warren, 2009). PPM monitoring and control activities have increased importance for portfolio success when the level of interdependency is high (Kopmann et al., 2015). Although recognized as important, the management of interdependences is acknowledged as an area of weakness for PPM (Elonen and Artto, 2003). Some organizations record interdependency information along with other attributes in a project database or spreadsheet which can be used to generate lists of dependencies or other visual representations. In practice, interdependency information is sometimes displayed on a dependency matrix grid to inform management and support decision making (Dickinson et al., 2001, Danilovic and Browning, 2007). Dependency matrices provide a structured format for identifying relationships between each possible pair of projects, however these displays do not readily identify multi-step dependencies. A similar matrix based tool, the design structure matrix, can assist with sequencing activities that are highly inter-related, such as in product development (Qian and Lin, 2014), but are not designed for use at the portfolio planning level (Hoyle and Chen, 2009).

To meet the challenges of PPM, especially as complexity and uncertainty increase, researchers are actively developing and evaluating new decision-making tools (Aritua et al., 2009). A number of researchers incorporate interdependencies in mathematical modelling systems for prioritizing project portfolios. Mathematical models become highly complex and unwieldy in large interdependent portfolios, prompting novel approaches for large portfolios (Abbassi et al., 2014), Simplifications are required for such complex models, for example one approach incorporates dependencies but assumes all dependent projects are selected (Angelou and Economides, 2008), highlighting one of the common problems with mathematical models; the simplifications required can obscure important factors (Zheng and Vaishnavi, 2011). This may be one reason such models have made little impact on PPM practice.

Bounded rationality and PPM decision making

The bulk of PPM literature assumes that decisions are made on a rational basis within a structured PPM process (Loch, 2016). However, some authors question this assumption and find that other influences on PPM decisions can result in less than rational outcomes (Eskerod et al., 2004, Christiansen and Varnes, 2008, Stingl and Geraldi, 2017). Humans also have a tendency for bias towards excessive optimism (Prater et al., 2017); however, a PPM process can address such human shortcomings by improving transparency in the decision-making process (Lovallo and Sibony, 2006). In addition, humans are subject to ‘bounded rationality’ (Simon, 1955), which limits their ability to interpret the large amounts of data required in PPM decision making, and results in decisions that are not always rational. The need to make decisions without complete and accurate information, the human cognitive limitations in interpreting the information, and the finite amount of time available to make decisions, contribute to the 'bounded rationality' that affects PPM decision making, especially in complex and dynamic environments.

Most PPM decisions involve human judgment, often in an executive review meeting or PRB where each individual's experience, diversity, and judgment contributes to a powerful team perspective for decision making. However, complex decisions are strongly affected by human cognitive constraints (Foreman and Selly, 2002, Stingl and Geraldi, 2017). Humans are limited in their ability to recognize interdependencies and resultant flow-on effects from their decisions and actions in complex systems. While human capabilities are limited, research suggests that visualization techniques can compensate for limitations in working memories (Tergan and Keller, 2005).

Managers are asked to make decisions based on increasing volumes of information (Shim et al., 2002), and the time available to digest and analyze the information is often limited (Agor, 1986, Dane and Pratt, 2007). Decisions made with inadequate time are likely to be made with limited evaluation of alternatives and exhibit lower decision quality (Ahituv et al., 1998, Janis and Mann, 1977, Svenson and Maule, 1993). For example, time pressure is a factor contributing to budget over-runs in project management environments (Williams, 2005, Cicmil et al., 2006). In this environment of incomplete information, limited cognitive capabilities, and limited time, PPM decisions are often affected by bounded rationality and therefore may not be optimal (Blichfeldt and Eskerod, 2008, Stingl and Geraldi, 2017). PPM processes and tools aim to alleviate one or more of these challenges to improve decisions – for example by filtering and formatting information in a way that aids interpretation in the time available and within human cognitive limits. Comprehensive computer-based decision support systems have been suggested, with the aim of streamlining decision making and thus making better use of decision-making time (Shim et al., 2002), and numerous studies have proposed complex simulations and mathematical algorithms to incorporate multiple criteria and considerations for portfolio decision making (see for example (Eilat et al., 2006, Ghapanchi et al., 2012, Zschocke et al., 2013, Fliedner and Liesiö, 2016)). Recognizing the limitations of purely computational models, some models also include processes for incorporating human input. For example, Lee and Kim (Lee and Kim, 2001) integrated expert input into a goal-programming solution through Delphi and analytic network processes, and an evolutionary model by Chao and Kavadias (2013) incorporates ongoing decisions, thus reflecting human decision making characteristics. However, while many highly computerized solutions have been offered, there is little evidence of the use of such methods in PPM practice (Urhahn and Spieth, 2014, Christiansen and Varnes, 2008, Heidenberger and Stummer, 1999, Cooper et al., 2004). Repeated studies indicate that managers make the decisions in practice, and that the use of appropriately designed visual displays of portfolio data is correlated with better portfolio outcomes. Such displays support team decision making (Mikkola, 2001), improve the ability of portfolio managers to ‘sense and respond’ and make decisions more efficiently (Haeckel, 2004), and better support the inclusion of managerial intuition in the decision process (Zheng and Vaishnavi, 2011).

Cognitive fit and data representation tools

The cognitive fit theory explains how the fit between the method used to represent data and the nature of the decision task affects the quality of the resulting decision (Vessey, 1991). Different types of data representations emphasize different aspects of the data (for example, tables usually provide symbolic representation while graphics may display spatial relationships), while the needs of decision-making tasks vary in the information required from the data. The decision maker must create a mental model to analyze the data with respect to the task to arrive at a solution. When the data representation and the decision-making task are aligned, this cognitive fit is proposed to enhance decision-making ability by enabling the decision maker to directly apply the interpretation of the data representation to the problem-solving task. However, when the two are not aligned, the decision maker must perform further conversions of the data in order to address the problem, resulting in higher cognitive load, lower decision accuracy, and higher time requirements.

A number of experimental studies provide support for cognitive fit theory. In manufacturing and business settings, better cognitive fit between a tailored visual representation and the task substantially reduces the time required to complete a task (Teets et al., 2010, Basole et al., 2016). Visualizations with better cognitive fit help address the problem of bounded rationality by making it easier to absorb information in limited time. In addition, three dimensional (3D) visualizations provide better results when higher levels of task integration are required, mirroring findings from a study of forecasting in an accounting setting that demonstrated that alignment between the data and task dimensionality (3D visualizations of multi-dimensional data) improved the quality of the forecast (Dull and Tegarden, 1999). Visual tools were custom designed to reduce the cognitive load on decision makers in a study designed to improve portfolio selection (da Silva et al., 2017). In another study, graphical representations of geographical adjacency and proximity in maps were found to provide increasing benefits as task complexity increased (Smelcer and Carmel, 1997). Cognitive fit was used to explain the relationship between buyer behavior and different web formats that display the same information (Hong et al., 2004), and an experimental study of knowledge and expertise visualization methods found that decision speed, but not decision quality, was enhanced when compared with tabular information (Huang et al., 2006). A fractional factorial experiment showed that graphs provided better fit in a study of bankruptcy predictions; the graphs provided integrative spatial information while preserving the characteristics of the underlying data. The cognitive fit model relies not only on the task and the data representation; the spatial visualization abilities and other individual differences are also at play in the relationship between the task, data representation, and quality of the decision (Smelcer and Carmel, 1997, Vessey, 1991, Vessey and Galletta, 1991).

Visual representations and decision making

The combination of human cognitive skills and visual representations of data that have strong cognitive fit with the decision problem have the potential to greatly enhance PPM decision making. Visual data representations that harness the executive decision makers' experience, intuition, and judgment will provide particular benefits in a human-centered decision environment (Zheng and Vaishnavi, 2011). Visual representations of data are shown to assist with the analysis of complex data (Mikkola, 2001) and help communicate and shape strategic thinking (Warglien and Jacobides, 2010). These visual representations can provide an effective format for representing and communicating information to support strategic decision making by illustrating complex multi-dimensional aspects of decision problems in a simple and powerful manner (Meyer, 1991). Visual information is cognitively processed while preserving spatial orientations and inter-relationships. Research has found that visual data displays can aid in the attention, agreement, and retention of strategic information (Kernbach and Eppler, 2010).

Improvements in computers and software-based tools offer many new methods for collecting and displaying information (Dansereau and Simpson, 2009, Williams et al., 2014). Human skills in analysis and pattern finding, combined with computer-generated graphics, produce a powerful and flexible cognitive system, taking advantage of the strengths of both humans and computers (Tergan and Keller, 2005).

The power of visualizations to support decision making is only beginning to be exploited, and there is a need for more research in this area (Warglien and Jacobides, 2010, Basole et al., 2016). Cognitive fit is important, and visual representations of information must be customized for the task to best facilitate decision making. Some decisions require visualizations that display multiple factors, capture historical events, and reveal complex relationships (Platts and Tan, 2004). Matrix displays have particular strengths in evaluating and sharing information (Bresciani and Eppler, 2010), and can present multiple types of information in ‘2½-dimensional’ displays that are very powerful if well designed (Warglien, 2010).

A wide range of software solutions can assist with PPM data management and decision making. These software solutions range from targeted utilities for creating specific graphical displays to comprehensive systems that aim to support all aspects of the PPM process. A visual ‘dashboard’ is often included in PPM solutions, and most support the development of visual data displays such as portfolio maps (Daniel et al., 2014).

Network maps as a visual PPM tool

While portfolio maps are a form of visual data representation that shows benefits when applied in PPM (Killen et al., 2008, Cooper et al., 2001), they have limitations in that they do not show the relationships between projects. Network maps, on the other hand, visually display relationships between nodes in a network and reveal accumulated network effects (Scott, 2008), and are easily created by software-based tools. Network maps can reveal patterns more clearly than verbal or matrix displays and have been shown to provide benefits for decision making in mathematics, biology, and economics (Hanneman and Riddle, 2005). Network displays are especially suitable for ‘spatial-traversal’ tasks; they facilitate following the ‘edges’ or connections between elements to understand paths and connectivity (Basole et al., 2016).A common form of network mapping, social network analysis (SNA), facilitates organizational decisions through displaying relationships between people or organizations (Cross et al., 2002, Anklam et al., 2005, Scott, 2008).

In complex project portfolios, interdependencies often exist in a web of interactions. Therefore network mapping displays, with their ability to visualize ‘webs’ of connections between nodes, may have high cognitive fit with the problem of understanding and managing project interdependencies. From a project portfolio management perspective, network mapping can be used to display each project a node, and the dependencies between projects can be shown through connections (via lines, or arrows) between projects to create a network. Using such network principles, a visual project map (VPM) format has been developed to visually display the interdependencies between projects. These maps have shown promise in exploratory organization-based studies as a method to improve the understanding of project interdependencies across a project portfolio (Killen et al., 2009, Killen and Kjaer, 2012). VPM displays can be created with the aid of network mapping software such as NetDraw (Borgatti, 2002) or NodeXL (Hansen et al., 2011). Figure 1 shows an example of a VPM type of display.

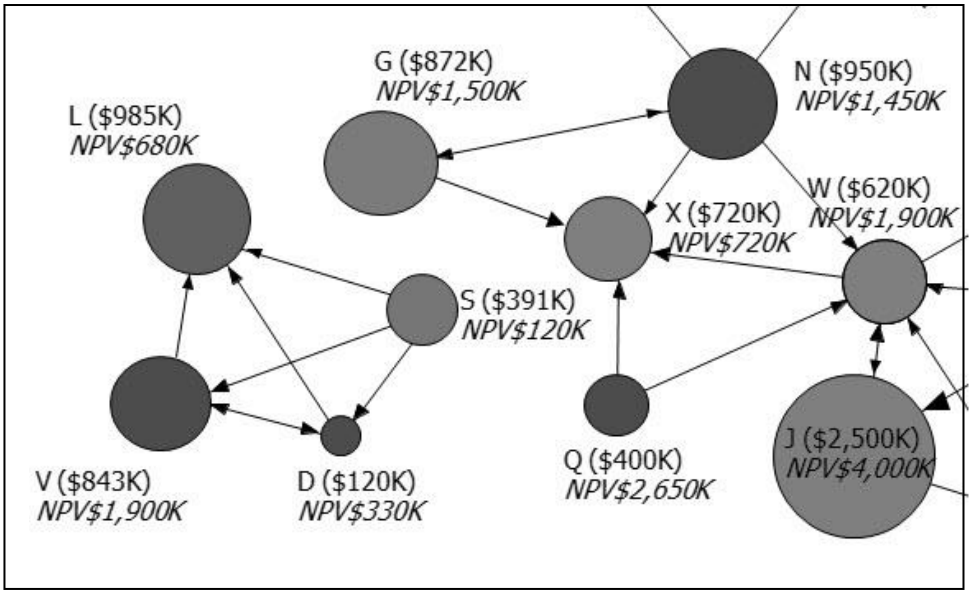


Figure 1: Portion of a visual project map (VPM).
Each circle is a project (circle size reflects investment, colors or shading represents strategic importance), and the arrows represent dependencies between projects. Labels provide project name, investment required and NPV.

Exploring network mapping as a tool for managing project interdependencies was initiated through two organization-based studies that confirmed the interest and indicated potential applications and benefits. Network mapping aided the analysis of projects, programs, and portfolios in a defense setting by highlighting the importance of projects upon which many other projects depended (Durant-Law, 2012). A pre-cursor study to the research reported in this paper tested the application of VPM in two organizations (Killen and Kjaer, 2012). The research involved collecting and categorizing project interdependency information, mapping the data in network displays, and gaining feedback from decision makers on the effects and applications for such maps. The study concluded that VPM could provide benefits as a decision-making or communication tool for PPM. Feedback from the organization-based studies suggested that VPM provided a superior way to ‘see’ relationships; however, such case-based studies are influenced by many uncontrollable factors, and further research was needed to understand the effects of introducing new methods to visualize interdependencies. The experimental study outlined in this paper was designed to further explore the influence of data visualizations on portfolio decisions by comparing VPM and other methods currently used in practice to represent interdependency data.

RESEARCH HYPOTHESES

The decision-making challenges presented by increasingly complex project portfolios are highlighted in the literature. There is an established need for better methods to evaluate project interdependencies to support PPM decision making. Previous findings that reveal positive correlation between the use of portfolio maps and PPM outcomes illustrate how visual data representation tools can assist with PPM decision making. A new network mapping-based data representation tool, VPM, has been introduced and applied in organizational settings; however, it is unknown how VPM and options for representing interdependency data compare in their ability to affect the resulting PPM decisions.

Visual and graphical data displays provide advantages when combined with human cognitive capabilities during decision making (Tergan and Keller, 2005), and these advantages are proposed to be stronger in displays with a higher degree of cognitive fit. Cognitive fit theory suggests that each type of data representation tool will have a different level of cognitive fit with the problem (Vessey, 1991). In this study, three different representations of interdependency data were compared for their ability to improve understanding of project interdependencies and enhance decision quality in complex project portfolios. The methods under investigation were (1) VPM – a new approach based on network mapping displays, (2) dependency matrices – matrix-based displays used in practice, and (3) tabular representations – a visualization based on current use of spreadsheets and databases that list dependencies in a column.

VPM displays, with an ability to directly represent the connections between interdependent projects and to visually reveal the multi-step dependencies that are not easily seen in the other displays, are proposed to have the highest degree of cognitive fit and therefore to contribute most strongly to decision quality.

Therefore, the first hypotheses addressed in this study are:

> H1: The type of tool used to evaluate project interdependencies is associated with the different levels of quality of the resulting PPM decisions in complex project portfolios.
>
> > H1(a): VPM displays are associated with better quality PPM decisions than the other tools in complex project portfolios.

Time pressure is another challenge highlighted in the literature; time pressure can have detrimental effects on decision-making ability (Janis and Mann, 1977, Svenson and Maule, 1993, Ahituv et al., 1998). As time pressures are often unavoidable, it follows that tools that reduce the perception of time pressure or the negative effects of time pressure will enhance PPM decision making. Visual data representations can allow data to be cognitively processed while preserving spatial orientations and inter-relationships (Meyer, 1991) and therefore may require less data conversion to evaluate inter-relationships, resulting in a reduction of the time required to complete a task (Teets et al., 2010). This study proposed that the different visual tools possess different degrees of cognitive fit with the task, and so provide different levels of time-saving benefits in the analysis of interdependencies. VPM displays are proposed to have the highest degree of cognitive fit and to alleviate time pressure better than the other tools. If users are more likely to feel they have enough time to make a decision with a particular tool, then that tool is more likely to provide benefits in less time, reduce the negative effects of time pressures, and lead to better decisions. The second and third hypotheses are:

> H2: The type of tool used to evaluate project interdependencies is associated with different perceptions of time adequacy.
>
> > H2(a): Users of VPM displays report higher levels of time adequacy than users of other tools.
>
> H3: Perception of time adequacy positively relates to the quality of the resulting decision.

A higher degree of cognitive fit should enhance the power of human cognitive capabilities to accurately recognize the interdependency relationships in the project portfolio. VPM displays are proposed to have the highest level of cognitive fit with the interdependency evaluation task, and should therefore result in better interdependency understanding. Therefore the fourth set of hypotheses is:

> H4: The type of tool used to evaluate project interdependencies is associated with different levels of understanding of the interdependencies in the portfolio.
>
> > H4(a): Users of VPM displays report higher levels of understanding of the interdependencies in the portfolio.

Improved understanding of the interdependencies in the portfolio is desirable because it should lead to better decisions. A system with better cognitive fit that enhances human cognitive capabilities to understand interdependencies is only of value if that understanding is translated into better decisions. We propose that the quality of the decision will be related to the level of understanding of project interdependencies. Therefore the fifth hypothesis is:

> H5: The level of understanding of project interdependencies is positively related to the quality of the decision.

Figure 2 displays the five hypothesized relationships between the type of tool used to visualize project interdependencies and the resulting decision quality.

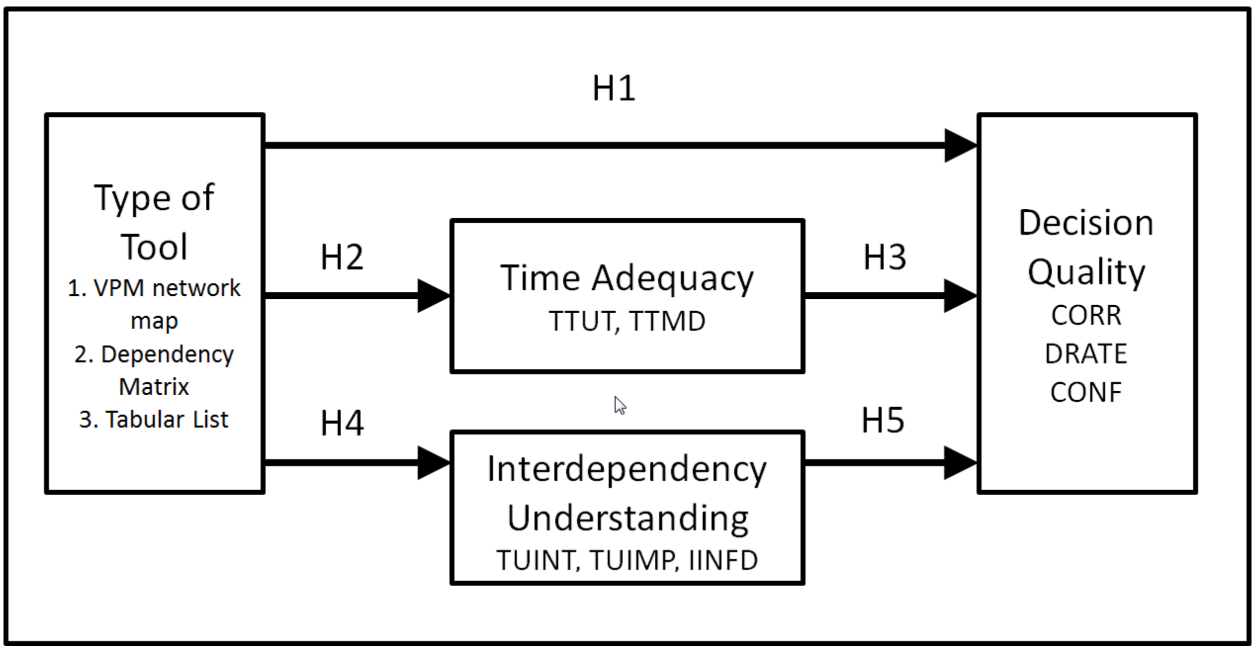


Figure 2: Conceptual model linking the type of tool, perception of adequacy of time, level of interdependency understanding, and decision quality.

RESEARCH METHOD

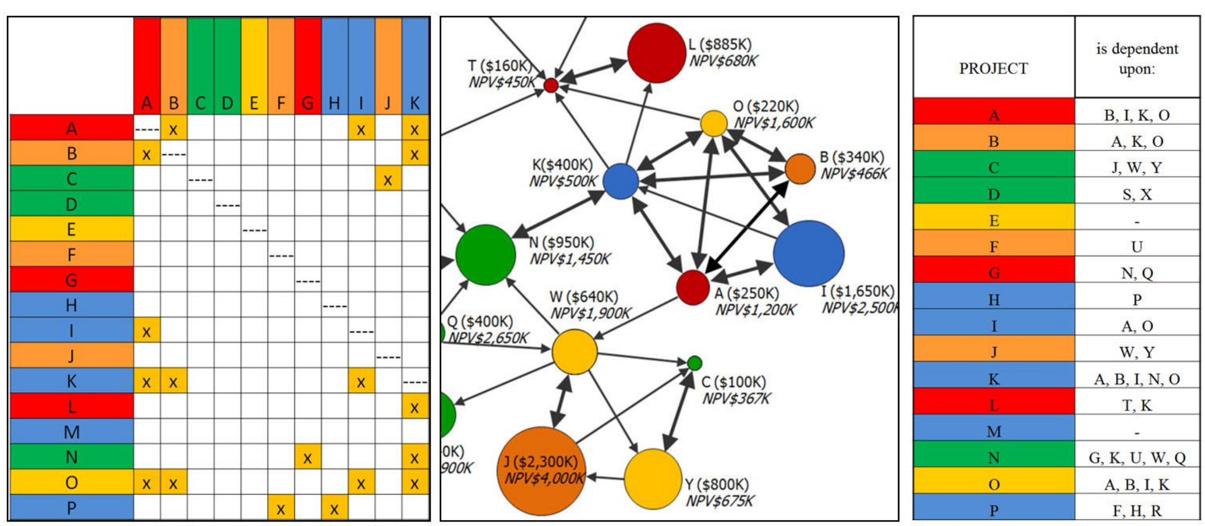
Methodology

A simulated decision task in a controlled classroom setting was used to test the five hypotheses. Although experimental research is common in fields like psychology, economics, or marketing, it is not common in project management or PPM research, and the research reported in this paper represents an exploratory application of experimental research in such settings. The few related studies reported in the literature include experimental approaches to simulate resource allocation and sharing decisions in a project environment (Bendoly and Swink, 2007), to understand decision-making processes and learning effects in the project and portfolio management domain (Arlt, 2011), to compare the fit between visualizations and context in business decision making (Basole et al., 2016), and to test the efficacy of a range of tools for product portfolio decision making (de Villiers et al., 2016).

Experimentation complements previously conducted organization-based research (Killen and Kjaer, 2012), and was selected in this study to provide a reliable and controllable environment where the effects of changes can be measured. The current study was designed to balance the principles of realism and simplicity as summarized by Grossklags (Grossklags, 2007). A degree of realism was included by proposing a plausible scenario based in a business environment. Simplifying the scenario enabled participants to focus on the central task, and the controlled setting removed many of the confounding factors that would impact research in an organizational setting.

Experimental data displays

The experiment evaluated and compared the use of different methods of presenting project interdependency data. Three different types of data displays were developed for this study: a dependency matrix, a network mapping display (VPM), and a tabular representation as shown in Figure 3. Each of the displays contains the same information, and each has been color coded to highlight the strategic importance of the projects in the portfolio. A rainbow spectrum was employed, with red and orange used to highlight highly strategically important projects, and green and blue used for projects that are less important strategically. In addition to strategic importance and dependency data, the scenario also included financial information (investment and projected return on investment). For the dependency matrix and tabular displays, this information was provided in columns (to simplify the picture, these columns are not shown in Figure 3). On the network mapping display, the financial information was shown as labels, and the size of the circles reflected the investment amount for each project (as shown in Figure 3).



Dependency Matrix: X in a cell = project in the row is dependent on the project in the column

VPM: Arrow points from a project (circle) that delivers something to the dependent project

Tabular: Lists each project and the projects they depend upon

Figure 3: Examples of data displays used in the experiments.
Portions of three visual displays of the same data. Colors indicate strategic importance. Identical financial data were provided on each display (see text for explanation).

The tabular representation and dependency matrix displays were based on approaches commonly used in industry to represent project interdependencies. The tabular representation presents project interdependencies in a single column as part of a spreadsheet. The dependency matrix display provides a deeper level of detail by highlighting dependency relationships in the cell corresponding to the pair of interdependent projects (in the row and column).

The newly proposed method, VPM, visualizes project interdependencies based on a network mapping approach. An increasing range of network mapping tools facilitate the creation of such displays, making it practical to consider the introduction of such displays to support PPM decisions (see for example (Borgatti, 2002, Hansen et al., 2011)). The VPM type of display (as per the sample in Figure 1) is proposed to have the highest level of cognitive fit with the interdependency analysis problem, as each interdependent set of projects is directly connected by an arrow, and as the multi-level interdependencies are also easy to visualize.

The experiment reported here was designed to reveal the potential influence of the type of data representation on the resulting decision. Visual displays were based on identical project interdependency data in each of these three formats and randomly assigned to research participants as detailed below.

Research design and experimental session detail

Postgraduate students enrolled in Masters-level programs participated in this study as part of a course in technology management. Students are often used as research subjects in experimental research and can provide relevant input when they have an appropriate background (Arlt, 2011, Bendoly and Swink, 2007, Dull and Tegarden, 1999, Vessey and Galletta, 1991). The student participants in this study had completed an engineering or technical undergraduate degree and were already familiar with project and portfolio management concepts from earlier modules in the technology management course, which aided their suitability as research participants. However, it must be acknowledged that the use of students may introduce bias as there may be a lower degree of diversity among the group and common source bias may result, and because they do not usually possess the same level of experience and maturity as practicing managers involved with PPM decisions. Participation in the research provided advantages to the students, as the topic is relevant in industry and served to augment and extend their education. As this research involved students, the university ethics clearance was obtained and the research was designed so that participation was voluntary and confidential.

The research design was pilot tested twice, first with seven participants and then with twelve. Following feedback from the pilot testing, the presentation of project data and the visual data displays were adjusted and the procedure for the warm-up task was refined. The pilot testing was also designed to capture results in five-minute increments to help determine the optimal time limit for the experiment, a 'trial and error' approach commonly taken in such research (Svenson and Maule, 1993). The pilot testing indicated that 15 minutes was about the right amount of time – enough for most students to absorb the data and make a decision but within a tight enough timeframe to highlight the effect of time pressure.

The experiment was embedded in an 80-minute educational session on the topic of PPM and project interdependency management. At the end of the experiment students were asked to fill out a short survey that collected data on the decisions made and on the participants' perceptions of time adequacy, confidence with the decision, and degree of understanding of the project interdependencies. The decision scenario was developed based on a realistic challenge – it asked students to reduce the budget by ten per cent by selecting one or more projects to cancel (remove from the portfolio). The scenario was complex due to the high number of interdependencies between projects in the portfolio.

During the class session, students were randomly assigned one of the three tools for their decision task, and were provided with a set of materials for the task using their assigned tool. A warm-up task conducted before the main decision task helped students learn about the use of their assigned tool, and aimed to reduce the learning effects inherent in the experiment by allowing students to move up the learning curve. During the main decision task, students evaluated identical data on the 26 projects in a generic project portfolio. The following information was provided for each project: investment and net present value projections, a rating for degree of strategic fit, and information on project interdependencies in one of three data display formats. For simplicity, all project interdependencies were assumed to be equal; varying types and strengths of relationships were not considered. Students were given 15 minutes to complete the decision task. In this time, they were required to review the information provided and decide which project or projects to cancel to trim the portfolio budget by ten per cent. During the decision process, students were asked to balance the following considerations with equal weighting: the interdependencies between projects and any flow-on effects from their decisions to cancel projects; the impact on strategic fit; and the return on investment. Although simplified for the purposes of this experiment, this type of scenario where multiple types of data must be balanced reflects the challenges faced by PPM decision makers.

Survey and item development

The research participants recorded their decision and provided responses for several items in a short survey immediately following the experiment. The eight items that were designed to test the hypotheses are listed in Table A1 in Appendix A. The items CORR and DRATE were rated based on each participant's decision. The remaining items employed anchored 5-point Likert scales to collect perception-based responses from the participants.

Three measures of decision quality were used to test Hypothesis 1 and determine whether the type of tool used to evaluate project interdependencies is associated with differing levels of quality in the resulting PPM decisions. Based on the decision entered by the participant, a binary rating (CORR) was created, with a value of 1 for the correct decision and 0 for any other decision. Another rating (DRATE) was rated on a scale of 1–5 based on how well the decision balances the required criteria and represents an optimal decision, with a rating of 4.5 or 5 representing the optimal decision and 1 the least optimal or most nonsensical decision. The rating acknowledged the gradation in decision quality, but required the use of judgment that could introduce bias. To reduce this bias, two researchers participated in a blind rating process (with no knowledge of the tool used or class session of the participant) and then discussed their decisions and agreed on the final ratings for DRATE. The third measure of decision quality was a self-reported item (CONF) that measured participants' confidence in their decision. Perception-based responses of this type are often used in survey research and are accepted as reliable indicators of reality. These three decision-quality ratings were compared with tool type to address H1 using a multiple comparisons test.

Hypothesis 2 proposed that the type of tool used to evaluate project interdependencies is associated with different perceptions of the time adequacy, and Hypothesis 3 proposed that perception of time adequacy positively relates to the quality of the resulting decision. To test H2 and H3, two items on the research participants' perceptions of time adequacy for understanding the tool (TTUT) and to make the decision (TTMD) were analyzed with respect to the tool type and decision quality measures.

Hypothesis 4 suggests that the type of tool used is associated with differing levels of understanding of the interdependencies. Three final items assessed whether the tool used was instrumental in the understanding of project interdependencies and portfolio effects of decisions (TUINT and TUIMP), and whether the interdependency information influenced the decision made (IINFD). Findings from these items are compared with tool type to address H4.

Hypothesis 5 proposes that the level of understanding of project interdependencies is positively related to the quality of the decision. The items TUINT, TUIMP and IINFD are correlated with decision quality measures to test H5.

Data collection and analysis

The experimentation was conducted in eleven postgraduate technology management classes between 2011 and 2015 and resulted in 480 valid survey responses from 493 students. Responses were considered invalid if participants did not identify which tool they used during the experiment or selected more than one tool; these invalid responses were ignored during the data analysis. The valid responses represented a random allocation of tools across the eleven class sections; 166 participants used a VPM display, 162 used the dependency matrix and 152 used a tabular representation. Although the experiment was designed to allocate the tools equally across the sample, the numbers are slightly different due to the use of eleven class sections where class numbers are not always divisible by three, and due to the removal of some invalid surveys.

Mean and standard deviations for the survey items are presented in Table A1 in Appendix A.

Hypotheses 1, 2, and 4 required comparison of responses for three different treatment groups (tool types). The method used to compare all pairwise results for the three tools was a multiple comparison statistical test (Hair et al., 2006). This compares each pair of respondent groups (i.e. VPM versus tabular representation; VPM versus dependency matrix; and tabular representation versus dependency matrix). The multiple comparison test adjusts for the number of statistical tests conducted, which is one of its advantages compared with a series of pairwise t-tests. Tukey's HSD (honest significant difference) test was selected for the analysis, as it is more robust than Bonferroni. The level of significance of the differences in means for the three tools is identified in figures 4 - 7 and tables B2 and B3 using the symbols *, **, and *** for findings that are significant at 0.050, 0.005, and 0.000 or better.

The multiple comparison test was also used to test for any significant differences in responses based on the class session. In addition, multiple comparison tests were conducted between pairs representing all combinations of the eleven classes. No significant differences were found between item responses based on the class session attended.

Bivariate Pearson correlations were used to test correlation between the 5-point scale items for hypotheses 3 and 5. Tests for normal distribution revealed acceptable kurtosis of the data; however, data for a few of the items were negatively skewed, and so nonparametric analyses were also conducted using Kendall's tau and Spearman test. These tests confirmed the significant relationships identified using Pearson's Chi squared tests with only minor differences between the Pearson results. Therefore, for simplicity the data have been reported using the Pearson format. All statistical results represent two-tailed analysis. Significance levels are reported for each correlation.

FINDINGS AND DISCUSSION

All but one of the primary hypotheses were supported by the findings. The only exception was that no significant difference was found between perceptions of time adequacy and tool use to support Hypothesis 2. The findings related to each hypothesis are detailed below.

Hypothesis 1: The three measures of decision quality were used to determine whether tool type is related to decision quality. Overall, 22 per cent of respondents arrived at the correct and optimal decision (CORR = 1) during the decision task. As shown in Figure 4, the percentage of research participants that made the optimal decision was highest for the group that used the network mapping VPM tool, with 33 per cent of the participants achieving an optimal decision in the time allowed. In contrast, 16 and 17 per cent of the decisions made using the other tools, the dependency matrix and the tabular representation, respectively, were optimal.

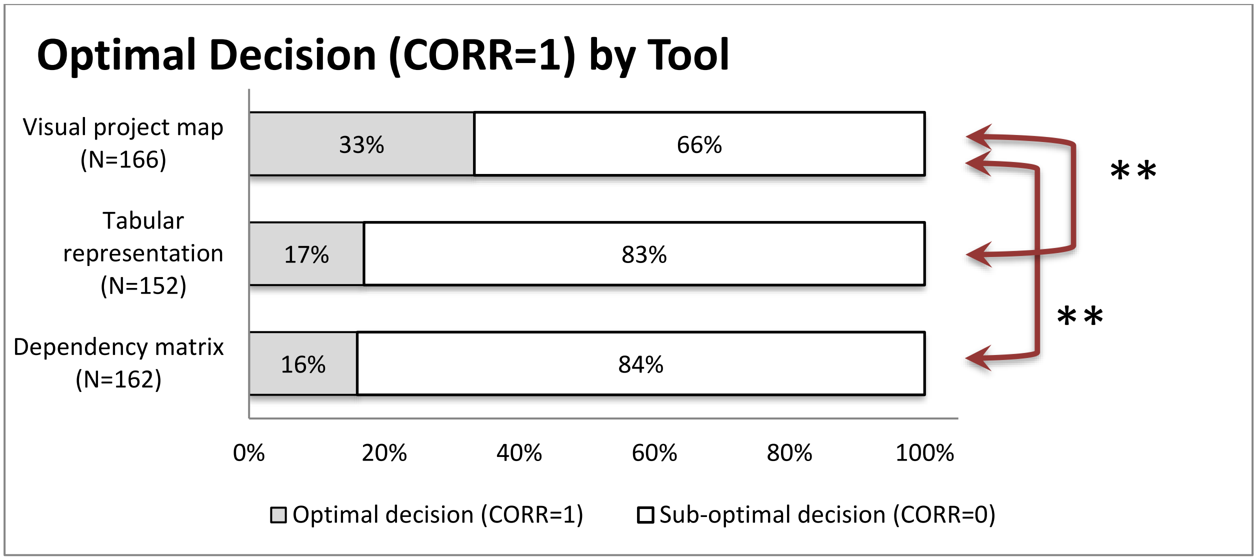


Figure 4: Percentage of optimal decisions (CORR=1) per tool type
(** indicates 0.005 or better significance of the difference between tools)

The difference in percentage of optimal decisions made when the VPM was used compared with decisions made when the dependency matrix was used (33%–16%=17%) is significant with a p-value of 0.001. The difference between the VPM and the tabular representation is also highly significant, with a p-value of 0.002. These results show that the VPM group had a significantly higher percentage of optimal decisions than the other two groups. However, there is no significant difference between the tabular representation group and the dependency matrix group (see Table B2 in Appendix B for further detail of the multiple comparison analysis).

An alternative view of the relationship between tool type and decision quality was developed using a rated degree of decision quality that acknowledges the continuum between 'best' and 'worst' decisions. Overall, the mean value for DRATE (rated degree of decision quality) was 2.84 with a standard deviation of 1.499. Figure 5 illustrates the mean values for DRATE for groups using each tool. The difference in average decision quality between the VPM group and the dependency matrix group is significant at the 0.001 level, as is the difference between the VPM group and the tabular representation group. There was no significant difference in decision quality between the dependency matrix and tabular representation groups.

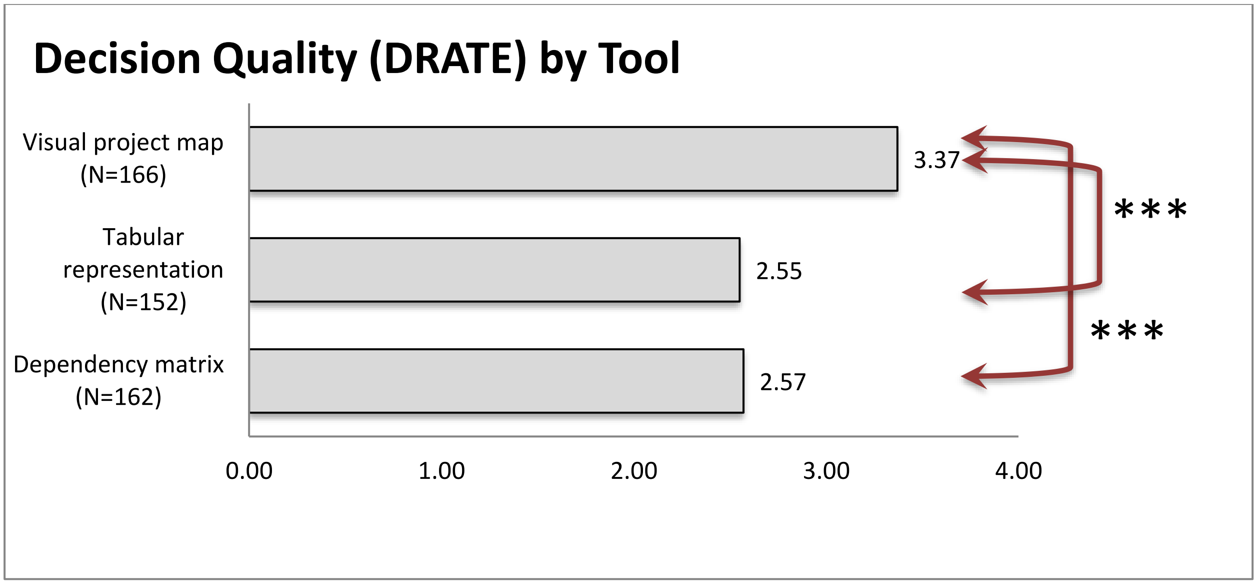


Figure 5: mean rating for decision quality per tool type (full sample)
(*** indicates 0.000 significance of the difference between tools,
see Table B2 in Appendix B for further detail of the multiple comparison analysis).

In addition, when considering only the participants who had a sub-optimal decision (CORR=0), the decision quality (DRATE) of those using the VPM tool was of higher quality than the other tools, as shown in Figure 6. This analysis shows that there were significant differences between tools and the decisions made with VPM were better, even when the correct decision was not made.

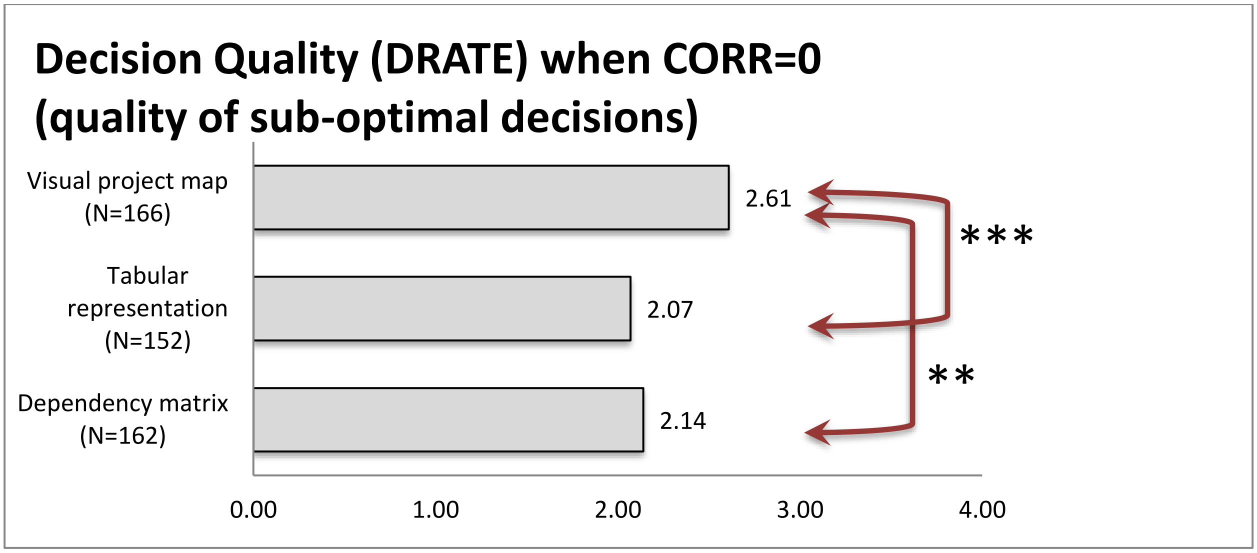


Figure 6: mean rating for decision quality per tool type
(based only on decisions that were sub-optimal (CORR=0))
(** indicates 0.005 or better significance of the difference between tools).

These first two measures of the quality of the decision, CORR and DRATE, are highly correlated. The mean value of DRATE for respondents where CORR=0 (not the optimal decision) was 2.26, whereas the mean value for DRATE when CORR=1 was 5.0 (mean difference of 2.74, sig 0.000).

The final measure of decision quality, CONF (participants' level of confidence in their decision), did not show any significant differences that corresponded to the use of one of the tools. However, the level of confidence correlated very significantly with the rated decision quality (DRATE) (Pearson 0.303, sig 0.000).

Overall, these findings support H1 and H1(a). The type of tool used to evaluate project interdependencies correlated with differing levels of decision quality as measured by CORR and

DRATE, and the use of VPM displays corresponded with the best decision quality results as hypothesized.

Hypothesis 2: H2 proposed that the type of tool used to evaluate project interdependencies is correlated with the perception of the adequacy of the time allocated to the decision task. Comparison of the perceptions of time adequacy with type of tool used did not reveal any relationships strong enough to statistically support H2 or H2(a).

Hypothesis 3: H3 proposed that perception of time adequacy is positively related to the quality of the resulting decision. As shown in Table B1 in Appendix B, decision quality correlated strongly with perceptions that time was adequate (p-value<0.001). Respondents who felt they had enough time to understand the tool used (TTUT) and to make decisions (TTMD) made significantly better decisions (p-value<0.001) and had higher confidence in their decisions (p-value<0.001).

Hypothesis 4: H4 proposed that the type of tool used to evaluate project interdependencies is correlated with the level of understanding of the interdependencies in the portfolio. Figure 7 compares the interdependency understanding items based on the type of tool used and provides strong support, showing significant differences between all pairs of users of each type of tool for the ability of the tool to enable understanding of interdependencies, TUINT, and the ability to enable understanding of impact on other projects, TUIMP. These two measures provide support for H4(a) as they show highest mean responses for VPM users, followed by dependency matrix users, with the users of the tabular representations reporting the lowest levels of attention and understanding. However, there were no significant differences between tools in the influence of the interdependency information on the final decisions.

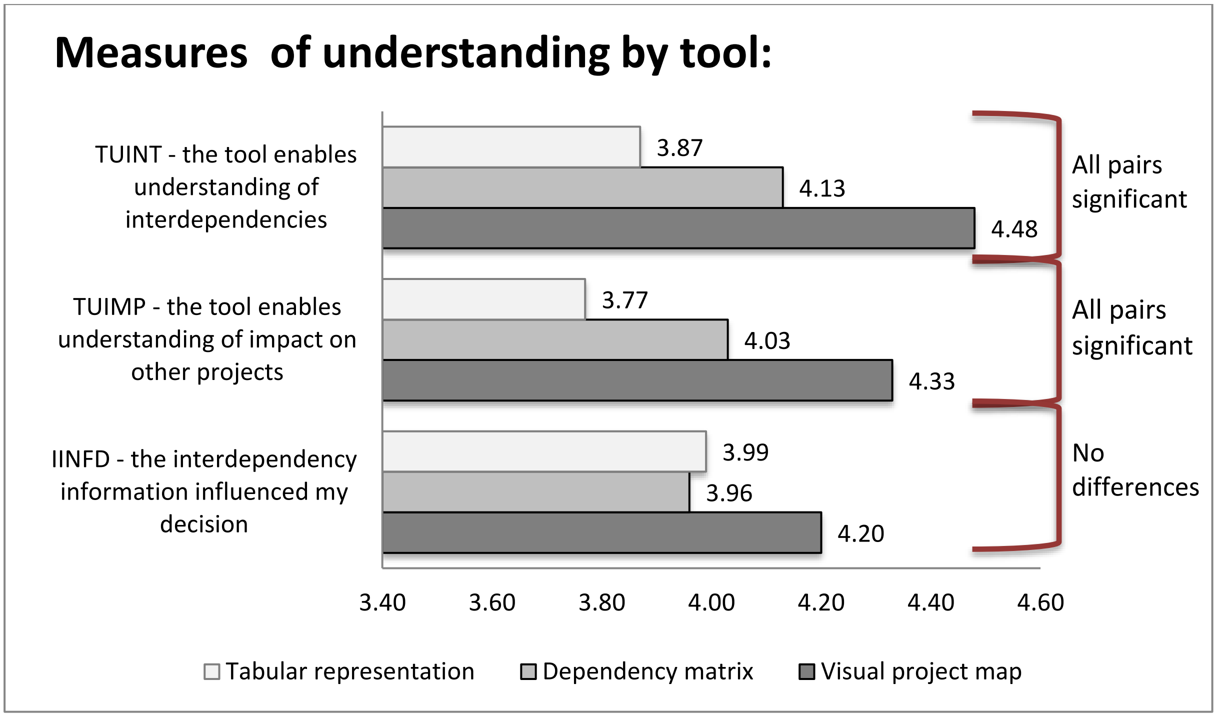


Figure 7: Mean responses on interdependency understanding and analysis by tool type
(see Table B3 in Appendix B for detail of the multiple comparison analysis including the levels of significance between each pair)

Overall, these findings provide strong support for H4 and H4(a), indicating that the level of understanding of the interdependencies differs significantly between the different tools and is highest for users of VPM displays. Although there are significant differences between the levels of understanding of interdependencies and their impact on other projects when using different tools as shown in Figure 7, there is no significant difference between the degree that the interdependency information influenced decisions (IINFD) when VPM is used. This may explain the weaker decision quality results for the users of dependency matrices and tabular representations; when a weaker understanding of project interdependencies is used to influence decisions it is likely to negatively affect the decision quality.

Hypothesis 5: Finally, as shown in Table B1 in Appendix B, all three measures of the understanding and analysis of interdependencies (TUINT, TUIMP and IINFD) show significant correlations (p-values<0.001) with the quality of decisions (DRATE) and the degree of confidence in the decision (CONF) providing strong support for H5.

SUMMARY AND CONCLUSION

Visual displays of data have the potential to improve decision makers' abilities to evaluate project interdependencies when making important portfolio investment decisions. Such PPM decisions are generally made by a team of diverse and experienced professionals who must consider large amounts of project data across the portfolio. Methods that enable decision makers to better understand information in less time will reduce the effect of the 'bounded rationality' that limits decision quality.

This exploratory research compared different methods of visualizing data on interdependencies between projects to determine whether the type of visualization affected the resultant decision. Following an earlier phase of exploration in organizations (Killen and Kjaer, 2012), the experiment-based study reported in this paper explored three different methods of representing project interdependency data and their relationships with decision quality in a simulated PPM decision scenario. The research proposed that the use of different data representations would result in differing levels of understanding of project interdependencies and different levels of decision quality. VPM displays were proposed to have strongest correlation with decision quality due to a stronger cognitive fit with the decision task; VPM displays provide a direct visual representation of links between projects and of the 'web' of interdependencies in a complex portfolio.

The findings, based on a sample of 480 experiments, support and extend research that demonstrates the benefits of visual and graphical data displays when compared with numerical and text-based information. The type of tool used to represent project interdependencies is associated with differing levels of PPM decision quality (in support of H1). The use of VPM, the newly proposed network mapping approach, is associated with the highest levels of decision quality, indicating that the cognitive fit between the representation and the task may be strongest and that VPM has the potential to improve the quality of PPM decision making for complex project portfolios.

The importance of reducing time pressure in decision making is highlighted by the strong correlation between adequacy of time and improved decision quality (in support of H3); however, no statistical difference was found in the perception of time adequacy between users of different tools (H2 was not supported).

The findings confirmed significant differences between tool type and the level of interdependency understanding and showed that users of VPM reported the highest levels of understanding (in support of H4). These findings suggest that the VPM displays may have the strongest cognitive fit with the task of understanding interdependencies. Finally, the research reveals a very strong relationship between the level of understanding of the interdependencies and the decision quality (in support of H5). These findings show that the use of VPM is most strongly correlated with high levels of understanding of project interdependencies and of the flow-on effects of project decisions across the portfolio, and suggest that this understanding may contribute to higher decision quality. The study also illustrates the power of combining human insight with visual data displays to support better decisions.

Limitations and implications for future research: The experimental design outlined in this study illustrates how an experiment-based study can be useful in PM and PPM research, especially as a complement to organization-based research. Although the research was designed to mitigate the limitations inherent in controlled experimentation, such limitations need to be acknowledged when interpreting the results. For example, the design of the experiment could bias results, and students may not reflect managerial decision making. In addition, the simplification of the scenario may skew the results and it is not known whether including additional factors such as risk or project sponsorship levels would affect the findings. The management of interdependencies is more complex than illustrated in the scenario, and different findings could result if the method is tested with additional types or multiple strengths of dependencies. Finally, this research measured the decisions made by individuals and this may not accurately reflect group decision making, which is central to PPM. Future experiments could test a different combination of factors and/or incorporate group decisions, and should aim to triangulate findings with organization-based research for improved validity and reliability.

Future research could also delve more deeply into understanding the cognitive fit between the visual displays and the decision task; while the theory of cognitive fit was used to hypothesize and explain results, this research did not explicitly test user perceptions of cognitive fit or explore the mental models employed during decision making.

Two aspects of the findings raise specific questions and suggest a need for further testing. First, although the study showed a clear relationship between time and decision quality, none of the tools provided significant benefits through increased perceptions of time adequacy. More research is required to determine whether and how data representation methods can alleviate the time pressure and how they can be designed to efficiently enlist human cognitive capabilities in processing visual information. In addition, the findings suggest that the degree to which the interdependency information was used to influence the decision was not aligned with the corresponding differences between the levels of understanding reported. This misalignment could explain some of the lower quality decision outcomes, and could be investigated further to better understand the link between the level of understanding and the degree of application of that understanding to the problem.

Previous research on VPM conducted in organizational settings shows that organizational culture is an important factor in promoting information sharing and communication to support decision-making processes and tools (Killen and Kjaer, 2012). This experiment-based study did not explore such factors and, although it was created to reflect decision challenges in organizations, such an experiment is not sufficient to draw conclusions about professional practice. However, as a complement to organization-based research, this experimental study has provided increased confidence in the findings through triangulation of the results. While the organizational study provided real-life experience and feedback on the use of VPM, due to the complexity of organizational environments it was not able to isolate the influence of VPM or to directly compare it with other methods. The research reported in this paper compensates for these limitations by using a controlled experimental setting where only one variable is adjusted (the type of data representation) and by analyzing and comparing the resulting decisions. The findings from the experiment reinforce the findings from the organizational research; both show benefits from the use of VPM in improving understanding of project interdependencies. Experiment-based studies are not common in PM and PPM research, but show the potential to complement and augment organization-based studies. Researchers should consider extending and refining experiment-based approaches to enhance PM and PPM studies in the future, while keeping in mind the importance of ‘real world’ organization-based studies. The experimental research reported in this paper has complemented and built upon previous organization-based research; without alignment to such research it will be difficult to gain confidence from an experimental study.

Implications for management: The findings of this study highlight the importance of fit between the methods or tools employed and the problem at hand, mirroring findings from PPM research that demonstrates the need to tailor methods and tools to each situation. The use of visual data representations is supported, with the caveat that management should carefully consider the types of information required to support decisions and ensure that there is a good cognitive fit with the aspects of the data emphasized by visual data representations. With respect to the management of project interdependencies, the findings suggest that management should investigate whether visual displays, VPM in particular, can provide benefits in their organizations. The research supports the design and/or selection of software tools that create visual data displays to aid PPM decision making, especially highlighting the need for tools to manage interdependencies. In addition, the strong relationship between perceptions of time adequacy and improved decision quality supports efforts to reduce time pressure in decision environments. Managers should bear in mind that these results are based on a simulated decision task in a classroom setting that does not represent the full complexity of an organizational decision.

In conclusion, a controlled decision experiment has highlighted the positive influence of visual displays of data on PPM decisions. The study complements earlier organization-based research that reported positive experiences in trials of network mapping visualizations of project interdependency data. In this experimental study, network mapping data visualizations are found to be associated with higher levels of understanding of project interdependencies and better decision quality than the tabular or matrix-based data representation methods, indicating that network mapping displays may have better cognitive fit with the task. These findings highlight the value of visual data representations in supporting strategic portfolio decision making, illustrate the value of designing data representations that are fit for the decision task, and suggest that network mapping data representations may have the potential to improve the quality of decisions in the management of complex project portfolios.

APPENDIX A

Table A1: Rated variables and survey items with descriptive statistics

Rating Label	Explanation of rated variable	Mean	Std. Deviation
CORR	Binary rating, 1 for correct or optimal decision, 0 for any other decision	0.22	0.417
DRATE	Rated decision on 5-point scale for the statement "The decision made balances the required criteria and represents an optimal decision"	2.84	1.499
Item Label	**Item statement for 5-point scale Likert response**	**Mean**	**Std. Deviation**
CONF	I am confident I have selected the best projects to eliminate	3.61	1.044
TTUT	Before the main task, I had enough time to understand the interdependency evaluation tool I was assigned	4.27	0.996
TTMD	I felt I had enough time to make this decision	3.66	1.178
TUINT	The tool that I used enabled me to understand the interdependencies between projects	4.17	0.989
TUIMP	The tool I used enabled me to understand the impact of my decision on other projects in the portfolio	4.05	0.988
IINFD	The interdependency information influenced my decision	4.05	0.988

Participants were presented with item scales anchored at the end- and mid-points for each of the items listed in Table A1. The following example illustrates the style of anchoring used in the data collection survey.

Item CONF: “I am confident I have selected the best projects to eliminate”

1	2	3	4	5
No, I am not at all confident I have selected the best projects		I think I probably selected an appropriate set of projects		Yes, I am very confident that the projects I selected are the best ones to eliminate

APPENDIX B

Table B1 outlines the correlations between items and the decision rating DRATE and the item CONF.

Table B1: Pearson correlations between decision quality measures and other items

	DRATE	CONF
TTUT	0.191 (sig 0.000)	0.325 (sig 0.000)
TTMD	0.175 (sig 0.000)	0.546 (sig 0.000)
TUINT	0.178 (sig 0.000)	0.358 (sig 0.000)
TUIMP	0.181 (sig 0.000)	0.407 (sig 0.000)
IINFD	0.243 (sig 0.000)	0.337 (sig 0.000)

Table B2: Multiple comparison of percentage of correct decisions (CORR) and decision quality (DRATE) by tool (Multiple comparisons Tukey's HSD test)

Dependent Variable, Tool Group I, Tool Group J			Mean Difference (I-J)	Sig
CORR	Visual Project Map	Dependency Matrix	0.171 **	0.001
	Visual Project Map	Tabular Representation	0.16 **	0.002
	Dependency Matrix	Tabular Representation	-0.011	0.972
DRATE	Visual Project Map	Dependency Matrix	0.7964 ***	0.000
	Visual Project Map	Tabular Representation	0.8179 ***	0.000
	Dependency Matrix	Tabular Representation	0.0214	0.991

Table B3: Multiple comparison of interdependency understanding items by tool (Multiple comparisons Tukey's HSD test)

Dependent Variable, Tool Group I, Tool Group J			Mean Difference (I-J)	Sig
TUINT	Visual Project Map	Dependency Matrix	0.345 **	0.004
	Visual Project Map	Tabular Representation	0.604 ***	0.000
	Dependency Matrix	Tabular Representation	0.259 *	0.048
TUIMP	Visual Project Map	Dependency Matrix	0.301 *	0.014
	Visual Project Map	Tabular Representation	0.563 ***	0.000
	Dependency Matrix	Tabular Representation	0.261 *	0.047
IINFD	Visual Project Map	Dependency Matrix	0.242	0.095
	Visual Project Map	Tabular Representation	0.218	0.156
	Dependency Matrix	Tabular Representation	-0.024	0.978

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