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Data Visualization of Budgeting Assumptions: An Illustrative Case of Trans-disciplinary Applied Knowledge

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Abstract[2]

Trans-disciplinary research combines different fields into new conceptual and methodological frameworks. In this study, the SECI model of knowledge creation, which consists of Socialization, Externalization, Combination, and Internalization conversion modes, is used to analyze the implementation of a structured budgeting visualization system by a trans-disciplinary team. Through applied research in implementing a global budgeting system, budgeting assumptions are made explicit through visualization, transforming the approach to the budgeting process and its accuracy. This visualization, in turn, is enabled by assumptions underlying revenue planning, business services and employee compensation, and a visual process. The system displays a stepped approach, indicated by icons, representing the tasks involved in the budget process. For example, the system requires uploading the previous year's information, setting the assumptions, calculating the suggested figures based on assumptions, and amending the proposed outcome. As adapted by Rice and Rice (2005), SECI is applied as the socialization of tacit-to-tacit budgeting assumption knowledge is solidified during the design phase of this transformation exercise. The externalization phase, in which budgeting assumptions are transformed from tacit to explicit, is evidenced during the configuration phase of the new system. The systemic collaboration results in the explicit assumptions being collectively leveraged across the regions during and after the "go-live" phase of system development. Finally, the internalization phase involves the explicit assumptions being transformed into new tacit knowledge as the experts evolve new assumptions derived from the transformation process. Semiotics provides variance information through hue, with, for example, darker colours indicating higher variances. This trans-disciplinary communication provides the means for increased efficiency and effectiveness. The resulting budget framework is visually validated through a heatmap by comparing the budgeting accuracy and assumption

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complexity between the different regions where it was implemented. In summary, value is added in developing a new data visualization process, focusing on the role of budgeting assumptions and using planning process visualizations. This approach improves communication efficiency, effectiveness, and understanding of budgeting while enhancing accuracy.

Keywords: Data Visualization, Trans-Disciplinary, Budget Assumptions, Knowledge Management, Socialization, Externalization, Combination, and Internalization

1. Introduction

Experts' tacit knowledge is often not shared and, therefore, lost when they leave an organization. Based on intuition and expert domain understanding, this embedded and complex knowledge is difficult for them to communicate to others, especially with those not part of their disciplinary field. One example of tacit knowledge is the set of underlying assumptions that experts have in relation to their domain of expertise, such as their beliefs developed from experience and the predictions, they make based on past performance and future expectations.

It is argued that visualization can facilitate sharing tacit knowledge with other experts, allowing it to be diffused within organizations and optimized once made explicit. Visualization can support making embedded and complex tacit knowledge explicit and more accessible, thereby enabling trans-disciplinary communication and action. For example, visualization can reveal patterns through design, colour, and typography in graphs, charts, and heat maps. Research by Daradkeh (2017) found that data visualization makes it easier to synthesize information and reduces information overload. Visualization also enables integration, verification, and the identification of trends. For example, during a clinical study, Bhavani, Visweswaran, Divekar, and Brasier (2019) used visual analytical representations to integrate their data and accelerate translational insights. Their results suggest that the visual analytical representation functioned as a method of acknowledging boundaries evolving through emergent stages, progressively helping to integrate diverse disciplinary knowledge. They observed that this enables team members from multiple disciplines to play primary and supportive roles in transforming the visual representation of the data, enabling the team to arrive at novel translational insights that can then be shared.

Furthermore, visualized automated workflows can facilitate knowledge sharing and learning with others in the organization. This also improves performance, data security, accuracy, and reliability and addresses inefficiencies in current processes. For example, de Haan (1999) found that the transparency of a step-by-step approach enabled the reliability of the process to be proved and validated. In another study, Nikulina (2020) found that organizations that used automated budgeting systems with assumptions had higher investment returns.

This study illustrates how visualization facilitates tacit knowledge management through trans-disciplinary communication.

2. Transdisciplinary Communication

Transcendent theoretical approaches can be produced by combining and fusing the results of different fields into a new conceptual and methodological framework (Rosenfield, 1992). Jantsch (1972) distinguishes five types of collaboration in knowledge production, namely multi-, pluri-, cross-, inter- and trans-disciplinary research, which differ in their organizational structures and degrees of collaboration. Goldman, Feldman and Miller (1982) defined interdisciplinary work as a generic, all-encompassing concept including all activities that juxtapose, apply, combine, synthesize, integrate, or transcend parts of two or more disciplines. Krehbiel, Gorman, Erekson, Loucks, and Johnson (1999) observed that interdisciplinary research involves feedback mechanisms that would remain undiscovered if each discipline is presented in isolation. Huutoniemi, Klein, Bruun, and Hukkinen (2009) describe the distinction between multidisciplinarity and interdisciplinarity as a conglomeration of disciplinary components versus a more synthetic attempt at mutual interaction, respectively. Both interdisciplinarity and transdisciplinarity seek to produce a kind of meta-knowledge. Trans-disciplinary research is an approach that transcends the narrow scope of disciplinary views by breaking down disciplinary boundaries, merging existing disciplines, and incorporating non-disciplinary knowledge from external stakeholders (Sahamie, Stindt, and Nuss 2012).

The approach adopted in this research is trans-disciplinary, with an emphasis on communication between the disciplines and how it is enabled by visualization. Cuthbert and Pearse (2021) found that data pattern visualization reduces complexity, as it enables interdisciplinary communication between data scientists and managers through the translation of statistical patterns into visualizations that enable actionable management decisions. The study focuses on implementing a structured budgeting workflow visualization system in a large multinational firm to improve budget accuracy and planning. Strategic management, business process analysis, information systems, knowledge management, and financial planning and budgeting are combined to enhance budget accuracy and strategic decision-making through a shared understanding amongst the multidisciplinary team. An event-based, model-driven system promotes communication, understanding, and planning through process visualization.

Semiotics refers to studying symbols and signs and their role in communication and was published by Saussure in 1915 (Siemers, 2016). Images, signs, and symbols assist in conveying messages. These messages are also universally understood across many disciplines. Yi, Kang, Stasko, and Jacko (2007) identified several information visualization categories: select, explore, reconfigure, encode, abstract/elaborate, filter, and connect. Kauppinen-Räisänen and Luomala (2010) found that colour conveys attention, aesthetics, and communication. Bertin used size, value, texture, colour, orientation, and shape to infer association, selection order, and quantity (Morita, 2011). De Freitas, Dias, Maculan, and Szwarcfiter (2021) explored depicting distance through graph colouring, which has applications in, for example, channel assignment in mobile wireless networks. Visual elements such as colour, line, shape, composition, and texture convey meaning. In a heat map, a darker hue indicates a more significant variance within the budgeting application; for example, the shading of red and green often depict a more significant negative (darker) and positive (darker) budgeting variance, respectively.

Data visualization graphically displays quantitative information, including cognitive understanding and interpretation. This enhances the innovative processing of data to generate insight and knowledge discovery rendering it a trending research field and industry practice (Akpan and Aguolu, 2019). For example, Padilla (2018) found that visualization supports working memory, bottom-up attention, schema matching, inference processes, and decision making. Alhadad (2018) used visualizing data to support judgment, inference, and decision-making in learning analytics. Chang, Ku, and Nguyen (2022) developed visualizations to gain insights into aspect ratings and customer satisfaction before and during the pandemic. Based on the insights from the interactive visualizations, they created a deep learning based natural language processing model.

Data visualization can combine the automatic processing capability of computer power with statistical analysis of big data, enhancing information visualization and human interaction and uncovering knowledge for problem solving and decision-making. Visualization is seen as both a mode of communication and a research methodology across disciplines. However, this interaction between disciplines needs to be facilitated, and Alhahad (2018) found that visual analytics design aided trans-disciplinary communication. A central premise of the case illustrated here is that open, transparent, flexible, and respectful trans-disciplinary communication enables experts to share their knowledge by making their data analysis assumptions transparent.

Research indicates several benefits arising from using visualization in transdisciplinary communication. Alhahad (2018) found that visualization supports inference, judgement, and decision-making and is influenced by visual attention, perception, and decision-making. Akpan and Akpan (2021) found that visual analytics contributes to diverse disciplines such as computer science, engineering, operation research, and management, helping researchers and practitioners in multidisciplinary fields to analyse multidimensional data, enhance data visualization and knowledge discovery, generate insights, and make informed decisions. According to Akpan and Akpan (2021), based on the number of research citations, computer science, followed by engineering and management research, were the fields most impacted by visual analytics. Patterson, Blaha, Grinstein, Liggett, Kaveney, Sheldon, Havig, and Moore (2014) found that data visualization enables users from different backgrounds to interact with data to gain insights, understanding, and knowledge to aid in decision-making. They present a set of six leverage points visualization designers can use to influence human cognition: (1) exogenous attention; (2) endogenous attention; (3) chunking; (4) reasoning with mental models; (5) analogical reasoning; and (6) implicit learning. In a real-world design problem, Joyce (2015) investigated how data visualization enabled an engineering trade-off decision. A structure with a complex and dynamic set of responses was investigated, and a parametric analysis of the various modes and beams resulted in 729 solutions. These were graphed on a two-axis scatter plot, with material usage additionally being depicted as a circle and various colours used to link family groups.

In other research, Bradel, Edert, Koch, Andrews, and North (2013) used large high-resolution displays for co-located collaborative sensemaking. Kumar, Verna, Sharma, Bhargava, Vahadane and Sethi (2017) focused on visualization techniques during product development, where mind maps enhanced interdisciplinary communication and collaboration. Liu, Jin, Yan, Tao and Lin (2019) uncovered previously hidden themes of movement in taxis through data visualization. Yi et al., (2007) found that information visualizations enabled decision makers to 1) select, 2) explore, 3) reconfigure,

4) encode, 5) abstract/elaborate, 6) filter, and 7) connect data. Akoglu, Tong, and Koutra (2015) utilised graph-based anomaly (outlier) detection as a visual interpretation during their survey of financial and computer traffic in real-world examples.

Moreover, in a public health setting, Lee, Kim, and Monsen (2015) explored time-oriented visualization techniques such as flow charts and decision trees, making knowledge transparent and improving patient outcomes. They found that well-designed data visualization communicates more efficiently and effectively, contributing to improved clinical data interpretation and better patient care monitoring and decision-making. Visualization also enabled the engineers to make better performance decisions through improved intuition when faced with many complex options (Joyce, 2015).

In this paper, a trans-disciplinary approach was applied to the case of a new budgeting system aiming to improve budgeting accuracy. This illustration focused on a budgeting transformation project in which budgeting assumptions were made explicit through trans-disciplinary communication between geographical regions the organization was active in and refined to improve overall budget accuracy. Scenario planning and sensitivity analysis, underpinned by an understanding of current processes and predictions, was enabled by saving different budget versions driven by different assumptions or dimensions. This honed the accuracy of budgets, as the best options can be communicated to others and further developed or progressed.

3. Knowledge Creation and Knowledge Sharing

Adesina and Ocholla (2019) embarked on a study to ascertain the most widely used knowledge management (KM) process framework. By analysing KM practice between 1995 and 2015, they found SECI to be the most prevalent model. The SECI process is a framework within KM, first developed by Ikujiro Nonaka (1994). This model – illustrated in Figure 1 - consists of four stages: socialization, externalization, combination, and internalization and relates to the impact of these stages on organizational learning, innovation, and knowledge sharing. The diagram below illustrates that the socialization phase involves tacit-to-tacit communication, passing knowledge through practice, guidance, imitation, and observation. The externalization phase involves tacit-to-explicit communication and is often challenging. The combination phase includes communication from explicit knowledge to explicit knowledge. Finally, internalization involves taking explicit knowledge back to tacit knowledge, embedding this through doing and internalizing the knowledge as one's own (Nonaka and Toyama, 2015).

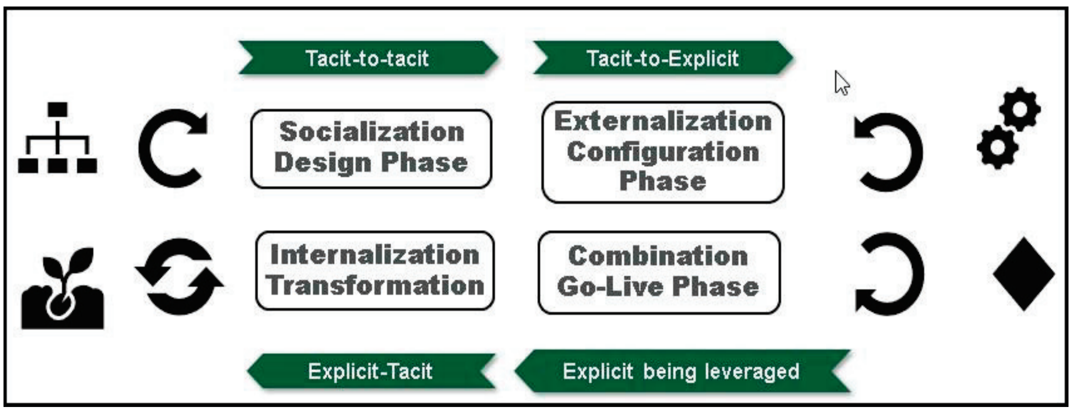

Figure 1 Adapted SECI model (Rice and Rice, 2005).

The SECI process is used in knowledge creation, knowledge sharing, and knowledge management. Knowledge creation refers to the collaborative construction of knowledge, while knowledge sharing refers to exchanging knowledge, skills, and experiences. Finally, knowledge management refers to identifying, organizing, storing, and disseminating information within an organization (Pearse, 2017).

Research on the application of SECI to visualization techniques in knowledge management is limited. Eberhard (2023) found that information visualization improves decision quality and speed with mixed effects on decision confidence. User and task characteristics act as moderators, while cognitive aspects mediate the process. Significantly, few studies are related to semiotics and visualizing budgeting assumptions, using these to facilitate improved accuracy.

This research investigated the role of visualization in the trans-disciplinary communication process of a diverse team to analyse whether visualization enabled the sharing of experts' tacit knowledge through the SECI knowledge management process.

4. Research Design

This paper is based on a case illustration in which the researcher was a participant observer in a financial transformation project that focused on visualization's role in making tacit budgeting assumptions explicit. The SECI framework explains the role of visualization through the socialization, externalization, and combination phases. The primary research design is a single case study that utilizes visualization to enhance budget accuracy, generating a better understanding based on empirical data.

The researcher studied how assumptions were harnessed and set up by budgeting subject matter experts from various geographical regions. These were included in algorithms that calculated the budgets based on billing patterns and collection seasonality assumptions. Analysis, synthesis, and observation compare these budgets to actuals through various visual representations, including profit and loss variance, in a heatmap format. This process was performed for a few previous years' data, progressively refining the assumptions and producing more accurate budgets with less variance (Figure 2)

5. The Illustrative Case Study

This study investigated the implementation of a budgeting and planning tool as part of a more comprehensive financial transformation project. Budgeting and planning are the domain of subject management experts. Transdisciplinary communication through heatmap visualization requires diverse fields to work together. This study illustrates how visualization facilitates tacit knowledge management through trans-disciplinary communication.

5.1 Socialization

Tacit assumptions, implicit in how budgeting domain experts think, were documented or translated into algorithms to generate explicit knowledge that could be shared for the collective benefit. For example, Taxes, Bonuses, Billable Hours, Billing Seasonality, Collection Seasonality, Productivity, Rates, and Realization Percentages needed to be coded into a budgeting system to calculate capital planning and employee compensation as revenue planning. If these estimations' reasoning could be made explicit, the planning capability would be retained when skilled experts leave the organization. Furthermore, assumptions could be tested, tracked, and challenged under different scenarios.

Budget variances are traditionally caused by incorrect assumptions, process problems (e.g., not recalculating once underlying assumptions change), inaccurate data starting points, and calculation errors. In addition, changing business conditions, market, political and regulatory changes, and even the number of days worked during the COVID-19 pandemic caused variances. Therefore, the team could exceed or underperform against the assumptions developed during the capital, employee compensation, and revenue planning phases.

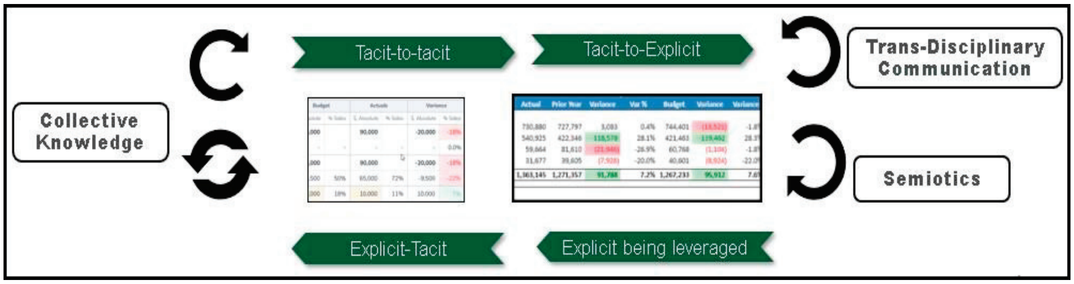

Figure 2. Communicating variance through a profit and loss variance heat map.

The project involved pre-populating the budget through verified prepared data loads and system setup data. General revenue planning, employee assumptions, and capital and project expense socialization were enabled using common symbols to create a shared understanding of the process and its outcomes. Using symbols in workflow also assists users in compliance. The researcher explored whether the regions that used more elaborate workflows communicated their workflow process more effectively and had fewer process errors.

These assumptions were structured in a workflow process configured by the expert to ensure the user performed the functions in the correct order so that mistakes related to users changing underlying assumptions later in the process are avoided. Task flow charts were set up, including one or more activities in a given order required to submit data correctly, with icons reflecting the various functions, for example, an upload, a report with editing capability, and a calculation. Several task flows could reflect the different entities' calculation model requirements. Below is an illustration (Figure 3) of a very standard planning process:

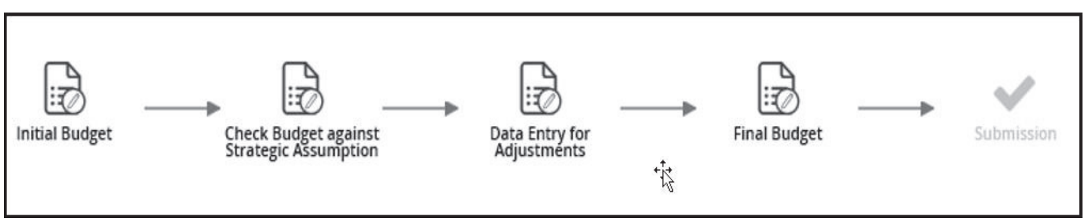

Figure 3: Standard planning process workflow.

These workflows automatically progressed work requests to the next person or approvers once the task was completed. Icon colouring reflected status. For example, yellow indicates progress, and green indicates the task is complete. White indicated that the task is not relevant to that entity or level. The visualized workflow process eliminated errors in previous years, where the underlying assumption was changed (for example, the number of business days) without rerunning all the subsequent calculations that used this base data. Generally, errors were reduced by locking in the workflow process compared to previous years and preventing errors made by changing underlying assumptions later. It improved tool reliability by eliminating spreadsheets and emails and enhanced control of the latest file version. Manual tasks were reduced.

5.2 Externalization

The various experts and stakeholders shared their budgeting assumptions. Next, the configuration team and subject matter budget owners captured these explicit assumptions in algorithms. The scenarios (actual and budgeted) were then drafted, merging the uploaded data, input data, and output reports for verification. The budgeting subject matter experts worked with the process analysts and the system configuration experts to ensure the underlying assumptions were calculated accurately. These were then reviewed by the budget owners and strategic management, which are not the subject matter experts developing the budget and represent a range of disciplines. The finance managers and budget owners confirmed the results through visual loss vatiances and other graphs and charts. By visualizing the assumptions (for example, comparing the budgeted versus actual results through a profit and loss report heatmap), the red areas indicating higher variances, were removed in iterations. Assumptions were made explicit during the externalization phase in the SECI process.

Visualization of the variance heatmaps across disciplines enabled users to improve various budget iterations, guided by eliminating the red variances. Eberhard (2023) found that visualization increases decision confidence. Abhinav, Boehme, Levine, Malony, and Schulz (2017) found that they improved judgement. Validation occurred through a continuous process whereby the variance heat maps between the budgeted and actual were run for each retrospective take-on year. Assumptions were adjusted and re-run to determine whether the different underpinning assumptions minimized the variance. Through this process, the red variance heat shades were progressively eliminated. The variance was minimized through visual verification using variance heatmaps, bar charts, and other graphs; this information was communicated to the broader stakeholders. Transdisciplinary communication through data visualization, therefore, enabled the budgeting process.

Understanding drivers of results in real-time and volumes of data easily translated into actionable insights drives value creation and expedited decision-making, facilitated by visualization. Time series analysis involves the analysis of historical data to identify patterns and factors affecting the outcome, for example, policies, economic growth, and client preference, to be used in assumptions and forecast planning. These trends are the basis for setting up the billing and collection waterfalls, as previous years' patterns help predict the cadence of billing and cash collection in future years. This meant that visualization was being used to enable the externalization process.

5.3 Combination

Budgets were finalized, calculations streamlined, and a trans-disciplinary team verified that all components were linked correctly. The resultant new assumptions were fed back into the cycle, improving budget accuracy. Tacit knowledge accumulated through years of experience in the industry (for example, through exposure to trends, regulatory changes, and benchmarking), intuition, and experience of the practice areas was made explicit.

In budgeting, the experts worked towards "reducing the red," which can be translated as reducing the budget estimation errors or variance. The areas that had higher variance generally needed to be underpinned by more defined assumptions. Variances were traditionally caused by incorrect assumptions, process problems (e.g., not recalculating once underlying assumptions change), inaccurate data starting points, and calculation errors: changing business conditions, market, political and regulatory changes. For example, during the pandemic, the number of days worked was affected, also causing variances.

Assumptions include information related to Billable Hours, Billing Seasonality, Collection Seasonality, Productivity, Rates, and Realization, and informed Revenue planning. In addition, assumptions on Capital and Employee Planning (for example, Taxes and Bonuses) were included.

Results were communicated in a profit and loss report through a heat map. In some regions, data about the relationships between billing and collection seasonality history was available and was explored.

During the combination phase, domain experts shared explicit beliefs between organization offices and regions. Once approved, they were aggregated, consolidated, and ready for final sign-off at a regional and group level. This cross-pollination ensured more accurate budgeting.

5.4 Internalisation

Internalisation involves the embedding of the assumptions within the region and the refinement of these by generating the results from the assumptions for a few consecutive years and refining these. Collaboration across the business and a single database provide visibility and control of corporate data to address multiple stakeholders. During this combination phase of the SECI process, the results are aggregated and compared to provide new insights.

Visualization was employed for the co-located collaborative sensemaking. This was also evidenced in a study by Bradel et al., (2013). The results are visualized in a heat map, charts, or graphs to give insights underpinning future budgets—visualization enhanced accuracy by internalizing shared assumptions and previous billing and collection patterns. The enablement of driver-based planning on a unified platform in a single data repository serves the needs of multiple diverse stakeholders, balancing the need for flexibility and simplicity. Through iterative SECI cycles, the assumptions are solidified, and the accuracy is improved.

6. Discussion and Implications

This research aimed to investigate the role of visualization in the transdisciplinary communication process of a diverse team and to analyse whether visualization enabled the sharing of experts' tacit knowledge through the SECI knowledge management process.

(1) This study illustrated that visualization was an enabler of transdisciplinary communication. Collaborative sensemaking and communication through visualization were also confirmed by Bradel et al. (2013) and Kumar et al. (2017).

(2) Visualization enables sharing of experts' tacit knowledge and embedding it in the organization as codified and explicit knowledge. This aligns with Lurie and Mason (2007), who assert that data visualization improves decision-making, facilitating information acquisition and integration.

(3) Variance heat map visualizations and symbol workflows enhanced budgeting accuracy and made budget assumptions explicit, demonstrating the potential of visualization to contribute to financial performance. Similarly, Nikulina (2020) found that organizations with explicit budget assumptions had better investment returns.

(4) The SECI knowledge management process was a valuable theoretical framework to apply to the data visualization of budgeting assumptions.

Furthermore, the application of the SECI model was extended through this research on improving budgeting assumptions and highlighting the potential role of visualization during the SECI knowledge creation and sharing phases.

7. Future phases of the study and research recommendations

This study has demonstrated the contribution of visualization to codifying and sharing knowledge. Future phases in this research project will involve forecasting, using techniques such as Monte Carlo simulations, regression analysis, and sensitivity analysis.

Previously Blackburn, Lurz, Priese, Göb, and Darkow (2015) used a predictive analytics approach to forecast demand in the process industry. Delen and Demirken (2013) found prescriptive analytics vital to supporting evidence-based management and optimised decision-making. Forecasting assisted through visualization assists organizations by enabling informed decisions about patterns or trends. By amending various dimensions, revenue planning is aided by understanding how this would change over time. Cash flow planning can assist organizations in avoiding cash flow challenges through a more in-depth understanding of their collection seasonality. Additionally, by modeling various scenario outcomes and applying them to different regions and practice areas, the deployment of resources can be maximized for the best outcome. Finally, forecast error analysis involves comparing the actual results to the forecasted results in the same manner applied during the budgeting phase to identify patterns such as over or underestimation linked to variables such as economic growth or interest rates. Recommendations for further research include widening these findings to other expert areas where tacit knowledge must be made explicit, communicated, and shared by various disciplines. The process analysis and visual verification methods could be used in other trans-disciplinary work. Budgeting and forecasting tools could automate application techniques such as regression analysis, Monte Carlo simulations, time series analysis, sensitivity analysis, and forecast error analysis to improve budgeting and forecasting assumptions.

8. Conclusion

This paper contributes by extending the SECI model to highlight the role of visualization during the phases of improving budgeting assumptions. The benefits of such visualization are illustrated through a case study. The challenges of the budgeting process are explained, including ways to address these. Overall, the paper includes insights into how visualization can improve the accuracy of the budgeting process and free up time for the experts to spend on value-adding activities.

Enhancing budgeting accuracy through visualization is an under-researched and neglected area. The main contribution of this paper is highlighting the value of variance heat map visualizations and symbol workflows in making budgeting assumptions explicit, thereby enhancing budgeting accuracy.

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