How Artificial Intelligence Can Affect Product Costing: A Look Into the Interaction Between Duration-Based Costing and Artificial Intelligence

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There has been much discussion regarding integrating Artificial Intelligence (AI) into accounting. This study focuses on the integration of AI with product costing models, most specifically with the Duration-Based Costing (DBC) model. The published literature regarding DBC shows that DBC can mimic or outperform an Activity-Based Costing (ABC) model that utilizes time drivers. Furthermore, the large amount of information that an ABC system utilizes can cause information overload, which DBC overcomes. DBC is a cost allocation technique that assigns overhead costs based on the production cycle time. The more time that a company spends producing a product, the more it will cost. DBC utilizes the concept "time is money." DBC is the model that looks at the larger picture. In other words, DBC looks at the forest overall whereas ABC looks at each individual tree in which the saying "cannot see the forest for the trees" applies to ABC. Therefore, this study aims to discuss how AI can integrate with DBC to provide a company valuable and quick cost information.

Keywords: duration-based, costing, DBC, artificial intelligence, AI

INTRODUCTION

Artificial Intelligence (AI) began in 1956 when John McCarthy and a few other computer scientists discussed future technological advances (Andresen, 2002). As computer systems have become more sophisticated, AI can now input and interpret data and has impacted accounting, taxation, auditing, and management accounting (Luo, et. al., 2018; Stancheva-Todorova, 2018; Chakraborty and Uddin, 2021; Hasan, 2022). AI has the potential to revolutionize management accounting decision-making and processes that could disrupt and change the roles of the management accountant. (Rikhardsson and Yigitbasioglu, 2018; Korhonen, et. al., 2020).

The barriers to AI in managerial accounting are resistance to change, organizational culture, lack of trust, and high costs of technology (Varzaru, 2022). Agency theory is applicable to the acceptance/resistance concerning AI. Agency theory analyzes the conflicts of interests between agents (employees) and principals (managers/owners) (Lambert, 2007). Company managers desire efficiency and effectiveness to increase profits. Employees desire job security and work balance. The concept of moral hazard in agency theory is applicable since employees may feel they have a duty to protect themselves, and thus, sabotage any effort to automate certain processes or incorporate quality problems in the information system (Tuttle, et. al., 1997; Dembe and Boden, 2000). Stancheva-Todorova (2018) and Makridakis (2017) discuss four types of responses to AI regarding employment. The first response is utopian in which people will welcome AI to replace them so that they can have more time for leisure and activities they enjoy. The second response is pessimistic in which AI will replace people to become second class, and as a result, people will lack motivation for work and decision-making. The third response is pragmatic in which people retain control over AI and utilize it to improve their skills and decision-making. The fourth response is doubting in which AI will never be a threat and human creativity will have priority over AI. The third response is logically the best response for accountants. Even NASBA saw the benefits of technology, and starting in 2024, the CPA exam will now incorporate technology that includes data analytics and AI to better prepare future CPAs (Roessner, 2023). Furthermore, the business school accreditation body, known as the Association to Advance Collegiate Schools of Business (AACSB), has adopted new accreditation standards where business schools must incorporate data analytics into the accounting curriculum (Surgent, 2019).

However, based on the research included in this literature review, AI could replace some accountants in analyzing data. This is a very important implication that needs awareness in business schools. Accountants, both present and future, need to learn to collaborate with AI instead of competing with it (Sutton, et. al., 2018). Accountants first need to be able to understand how AI works to be able to collaborate with it. Sutton, et. al. (2018) discuss the ethical ramifications of AI in which they question whether it is possible to have too much technology replacing people. Another ramification is whether a company properly programs the technology and has the proper security. This could lead to the ethical dilemma concerning whether society will be better off (Sutton, et. al., 2018). However, other researchers have argued that a properly programmed AI system that follows accounting rules will achieve more consistent, timely, and reliable accounting information (Bose, et. al., 2022). Although there is the cost to implement and program AI, it does have the potential to minimize accounting costs since some tasks will be automated. However, a potential downfall of AI is too much reliance on AI, especially when the system is hacked and no person is there as backup (Bose, et. al., 2022). However, not everything in accounting can be digitized (Korhonen, et. al., 2020). If a process is digitized when it should not be, it will lead to increased costs and inefficiency. This is the main reason accountants need to learn how to collaborate with AI, understand what can be automated, and properly maintain it, which means accountants will still be necessary and cannot be entirely replaced by AI. The accountants that might be replaced will most likely be the ones who do not want to adapt, rejuvenate their knowledge, and collaborate with AI. From the management accountant perspective, one way to collaborate with AI is to utilize what other researchers have done in integrating managerial accounting data analytics with the four perspectives of the balanced scorecard (Appelbaum, et. al., 2017). If a company can incorporate AI into its balanced scorecard, management accountants could effectively maintain AI, which will provide effective and efficient information for decision-making that an AI system could provide.

Since AI can be incorporated into management accounting, the purpose of this study concerns integrating AI with Duration-Based Costing (DBC). DBC has been created to simplify Activity-Based Costing (ABC) by providing overhead cost assignments close to those of an ABC system using time drivers (Lelkes, 2009, 2017; Lelkes and Deis, 2013). DBC consists of only one stage as opposed to two stages in ABC. The information needed for DBC is the production cycle time, the number of production runs, and the total overhead (or, resource cost). This means that activities and their associated drivers do not have to be identified. There is much less information overload in the DBC system. The production cycle time for each product is an observed value from when the materials are requisitioned to when the product is completed. Because of that, the production cycle time encompasses more than labor hours of the traditional systems.

The main concept in DBC is that the time spent in producing a product or performing a service causes costs to incur. Hence, it utilizes the concept "time is money." If a company can analyze its processes to reduce the cycle time, it will reduce costs, and thus, increase profits. DBC is the model that looks at the larger picture using the product cycle time. DBC looks at the overall picture whereas ABC looks at each individual activity, which can be cumbersome and cause information overload (Lelkes, 2009). Additionally, if a company wants to separate fixed and variable overhead costs, it can use Modified Duration-Based Costing in which variable and fixed overhead costs are separated with the variable overhead costs are assigned using the production cycle time as in DBC and the fixed costs are allocated using the number of production runs (Lelkes, 2015). DBC and MDBC has been applied to a Fortune 500 firm (Lelkes and

Krueger, 2020) and to a bank (Lelkes and Krueger, 2021). Finally, DBC has been incorporated into MyABCM® software that is used as an extension to Enterprise Resource Planning systems such as SAP, Oracle, and Microsoft (Lelkes, 2023). Thus far, not much discussion exists concerning integrating AI with DBC, which is the purpose of this article.

DURATION-BASED COSTING MODEL ILLUSTRATION

The DBC model used to assign overhead cost to a product or service (Lelkes, 2009, 2017; Lelkes and Deis, 2013) is as follows:

$$T_A = C\beta_A\lambda_A, \text{ for } A = 1,..., k, \tag{1}$$

where, T_A = the overhead cost for Product A
C = the cost per unit of time
β_A = the production cycle time for Product A
λ_A = the number of production runs, or units, for Product A

Equation 1 states that the overhead cost T_A assigned to Product A (for A = 1,…, k) is the cost per unit of time C multiplied by the production cycle time β_A for Product A, which is then multiplied by the number of production runs (or, units) λ_A for Product A. Table 1 shows a simple example to illustrate DBC. For brevity, an ABC system is not shown for comparison since prior research has already done that (Lelkes, 2009, 2017; Lelkes and Deis, 2013).

TABLE 1
ILLUSTRATION OF DBC

	Number of Production Runs	**Production Cycle Time**	**Total Time**	**Overhead Cost Assigned**
Gas Grill	1,000	4.15	4,150	$57,479
Pellet Grill	2,000	3.16	6,319	$87,521
	3,000		10,469	$145,000
Total Overhead Cost	$145,000			
Total Time	10,469			
Cost per Unit of Time	$13.85			

Table 1 shows two products: Gas Grill and Pellet Grill. The Number of Production Runs can be a batch of units or only one unit. The Production Cycle Time is an observed value where each grill is clocked from the time raw materials are requested until the grill is complete. The Gas Grill is clocked at 4.15 hours per run and the Pellet Grill is clocked at 3.16 hours per run. The Total Overhead Cost (or, resource cost) is $145,000. The Total Time of 10,469 hours is found by first multiplying the Production Cycle Time by the Number of Production Runs for the Gas Grill (4,150) and then the Pellet Grill (6,319), finally adding both times up. The Cost per Unit of Time of $13.85 is the Total Overhead Cost of $145,000 divided by the Total Time of 10,469. The Overhead Cost Assigned to the Gas Grill of $57,479 is equal to the Cost per Unit of Time ($13.85) multiplied by the Total Time for the Gas Grill (4,150). The Overhead Cost Assigned to the Pellet Grill of $87,521 is equal to the Cost per Unit of Time ($13.85) multiplied by the Total Time for the Pellet Grill (6,319).

The Modified DBC (MDBC) model contains two components, one variable and one fixed, (Lelkes, 2015) is as follows:

$$T_A = C^V \beta_A \lambda_A + C^F \lambda_A \text{ for } A = 1,..., k, \quad (2)$$

where, T_A = the overhead cost for Product A
C^V = the variable cost per unit of time
β_A = the production cycle time for Product A
λ_A = the number of production runs, or units, for Product A
C^F = the fixed overhead cost per production run, or per unit.

Equation 2 states that the overhead cost T_A assigned to Product A (for A = 1,…*k*) is equal to the variable portion plus the fixed portion. The variable portion is equal to the variable cost per unit of time C^V multiplied by the production cycle time β_A for Product A, which is then multiplied by the number of production runs λ_A for Product A. The fixed portion is equal to the fixed overhead cost per production run (or, per unit) C^F multiplied by the number of production runs λ_A for Product A. Table 2 illustrates MDBC.

TABLE 2
ILLUSTRATION OF MDBC

	Number of Production Runs	**Production Cycle Time**	**Total Time**	**Variable Overhead Cost Assigned**	**Fixed Overhead Cost Assigned**	**Overhead Cost Assigned**
Gas Grill	1,000	4.15	4,150	$37,659	$16,667	$54,326
Pellet Grill	2,000	3.16	6,319	$57,341	$33,333	$90,674
	3,000		10,469	$95,000	$50,000	$145,000

Variable Overhead Cost	$95,000
Total Time	10,469
Variable Cost per Unit of Time	$9.07
Fixed Overhead Cost	$50,000
Fixed Cost per Production Run	$16.67

Of the $145,000 in Total Overhead Cost shown in Table 1, Table 2 shows that $95,000 of it is variable and the remaining $50,000 is fixed. The Variable Cost per Unit of Time of $9.07 is the Variable Overhead Cost of $95,000 divided by the Total Time of 10,469. The Fixed Cost per Production Run of $16.67 is the Fixed Overhead Cost of $50,000 divided by the Total Number of Production Runs of 3,000.

The Variable Overhead Cost Assigned to the Gas Grill of $37,659 is equal to the Variable Cost per Unit of Time ($9.07) multiplied by the Total Time for the Gas Grill (4,150). The Variable Overhead Cost Assigned to the Pellet Grill of $57,341 is equal to the Variable Cost per Unit of Time ($9.07) multiplied by the Total Time for the Pellet Grill (6,319).

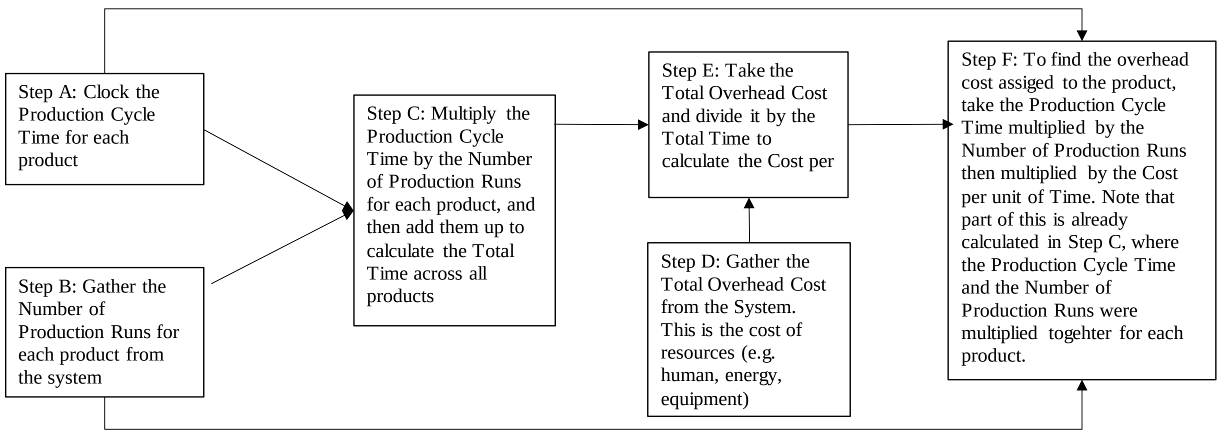
The Fixed Overhead Cost Assigned to the Gas Grill of $16,667 is equal to the Fixed Cost per Production Run ($16.67) multiplied by the Number of Production Runs for the Gas Grill (1,000). The Fixed Overhead Cost Assigned to the Pellet Grill of $33,333 is equal to the Fixed Cost per Production Run ($16.67) multiplied by the Number of Production Runs for the Pellet Grill (2,000).

The Total Overhead Cost Assigned to the Gas Grill and to the Pellet Grill is the sum of the Variable Overhead Cost Assigned and the Fixed Overhead Cost Assigned.

INTEGRATING ARTIFICIAL INTELLIGENCE WITH DURATION-BASED COSTING

Figure 1 provides a diagram of the process to assign overhead using DBC. This diagram applies to both a manual DBC system and an automated DBC system.

FIGURE 1
DIAGRAM OF HOW DBC WORKS



All of the steps to calculate DBC can be automated using AI. For instance, to find the production cycle time manually, a cost accountant will manually clock each product from when materials are requisitioned to when the product is completed. A company can use AI to clock each product, which will save time and money for the company. DBC can be programmed into an ERP system and AI to automate the entire cost assignment process. In a manual costing system, DBC outperforms ABC in data gathering and has less complex information input and output than ABC. In an automated costing system that will gather data for managers, DBC will still outperform ABC because a DBC system will generate easier to understand output for decision-making.

DISCUSSION AND CONCLUSION

This study discussed the implications of AI and how it can be integrated with DBC. Even in a fully computerized data gathering and analysis system, DBC wins over ABC in the amount of information generated. Prior research has discussed that ABC can cause information overload given all the activities that are required to be identified (Lelkes 2009, 2017; Lelkes and Deis 2013). When management generates reports from the system under ABC, much information will be provided, and many times it will be cumbersome for management to use in decision-making. For DBC, each activity does not need to be known, which is replaced by the production cycle time for each product. DBC can work with and be incorporated into AI and ERP systems to allow for accurate product (or service) costing. Managers can analyze each cycle time to see if the process time can be improved to reduce costs. AI and ERP systems will help managers in finding the most efficient way to reduce the cycle times to get products completed more timely and less costly. Accountants need not fear losing their jobs to AI as long as they learn to adapt and collaborate with AI.

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