ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

2025 REFEREED PROCEEDINGS

FEDERATION OF BUSINESS DISCIPLINES

March 2025
Tulsa, Oklahoma

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

2025 Refereed Proceedings

Tulsa, Oklahoma

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ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

CONGRATULATIONS!

Recipient of the ABIS 2025 Federation of Business Disciplines

Distinguished Paper Award

Taking a Multidisciplinary Approach to Introducing AI

Jason W. Powell, Northwestern State University of Louisiana
Ronnie Abukhalaf, Northwestern State University of Louisiana
Njeri S. Ngacha, Northwestern State University of Louisiana
Weiwen Liao, Northwestern State University of Louisiana

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

Association of Business Information Systems

ABIS 2025 Program Overview

Thursday March 20, 2025

7:30 a.m. – 10:00 a.m.	**ABIS & ABC-SWUS Joint Breakfast**
8:30 a.m. – 10:00 a.m.	Session A: **ABC-SWUS & ABIS Joint Session – Distinguished Paper Presentations**
10:30 a.m. – 11:45 a.m.	Session B: **AI and Information Systems: Opportunities, Risks, & Challenges**
11:45 a.m. – 1:30 p.m.	**Lunch on your own** ***Executive Board Meeting (by Invitation)**
1:30 p.m. – 3:00 p.m.	Session C: **Information Systems: Theory and Practice in Action**
3:30 p.m. – 5:00 p.m.	Session D: **Information Systems: Workshop**
5:30 p.m. – 7:00 p.m.	**FBD Presidential Welcome Reception**

Friday March 21, 2025

7:30 a.m. – 8:30 a.m.	**ABIS & ABC-SWUS Joint Breakfast**
8:30 a.m. – 10:00 a.m.	Session E: **ABIS Business Meeting *All Members Welcome***
10:30 a.m. – 12:00 p.m.	Session F: **Contemporary Topics in Information Systems**
12:00 p.m. – 1:30 p.m.	**Lunch on your own**
1:30 p.m. – 3:00 p.m.	Session G: **Information Systems: Tips, Tools, and Techniques**
3:30 p.m. – 5:00 p.m.	Session H: **Multidisciplinary Perspectives Regarding (Generative) AI**

CONGRATULATIONS!

Recipient of the 2025 FBD Outstanding Educator Award

Kimberly Merritt

Oklahoma Christian University

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

March 20, 2025
(Thursday)

7:30 a.m. – 8:30 a.m.	Council Oak A

ABC–SWUS and ABIS Joint Breakfast

We invite ABC-SWUS and ABIS Associations presenters and members to enjoy breakfast together!

ABC-SWUS or ABIS Association Name Badge Required for Entry

8:30 a.m. – 10:00 a.m.	Joint Session with ABC-SWUS	Council Oak B

SESSION A **ABC-SWUS and ABIS Joint 2024 Distinguished Paper Session**

Session Chairs: **Ashton Mouton**, Sam Houston State University
Mahesh S. Raisinghani, Texas Women's University

ABC-SWUS Distinguished Paper: *What Predicts Engagement on LinkedIn? A Study of Four Variables*
Daniel Usera, University of Texas at Arlington
Natalie Durham, University of Texas at Arlington

ABIS Distinguished Paper: *Taking a Multidisciplinary Approach to Introducing AI*
Jason W. Powell, Northwestern State University
Ronnie Abukhalaf, Northwestern State University
Njeri S. Ngacha, Northwestern State University
Weiwen Liao, Northwestern State University

10:00 a.m. – 10:30 a.m.	Sequoia - Exhibit Hall

FBD Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

10:30 a.m. – 11:45 a.m.	Council Oak B

SESSION B **AI and Information Systems: Opportunities, Risks, & Challenges**

Session Chair: **Carla Barber,** University of Central Arkansas

AI – All In? An Analysis of Student Use and Perceptions of AI Usage in College
Lori Soule, Nicholls State University
Sherry Rodrigue, Nicholls State University
Carla Barber, University of Central Arkansas
Betty Kleen, Nicholls State University

Confronting Challenges Due to the Rise of AI Usage in Discovery
Carmella Parker, Northwestern State University
Mary Fair, Northwestern State University

March 20, 2025
(Thursday)

10:30 a.m. – 11:45 a.m. – continued	Council Oak B

Criminology, Cybercrime, Education and AI - working together?
Elizabeth Prejean, Northwestern State University
Vianka Esteves Miranda, Northwestern State University
Eddie Horton, Northwestern State University
Danny Upshaw, Northwestern State University
Daniel Gordy, Northwestern State University

Run Your Own Personal AI Model
Eddie Horton, Northwestern State University

11:45 a.m. – 1:30 p.m.	**Lunch on your own**

ABIS Executive Board Meeting and Luncheon by Invitation Only (Location: Ficus Boardroom)

1:30 p.m. – 3:00 p.m.	Council Oak B

SESSION C **Information Systems: Theory and Practice in Action**

Session Chair: **Marcia Hardy**, Northwestern State University

Assessing the Impact of Computer-Based Interruptions on Task Performance an Eye-Tracking Experimental Study
Ziyi Niu, Eastern New Mexico University
George Kurian, Eastern New Mexico University
Ying Yan, Eastern New Mexico University

The Applications and Viability of ARIMA Modeling Using Current Employment Statistics
Joseph Adams, Tyler Junior College
Jason W. Powell, Northwestern State University
Curtis Penrod, Northwestern State University

Using Business Data to Identify Victims of the Tulsa Race Massacre
Traci Auston, Sam Houston State University

Integrating Quality Management 4.0 with AI and Machine Learning
Mahesh S. Raisinghani, Texas Women's University
Leilani Uttenreither, University of Maryland Global Campus

3:00 p.m. – 3:30 p.m.	Sequoia - Exhibit Hall

FBD Coffee Break

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ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

March 20, 2025
(Thursday)

3:30 p.m. – 5:00 p.m.	Council Oak B

SESSION D **Information Systems: Workshop**

Session Chair: **Mahesh S. Raisinghani,** Texas Women's University

The Journey to Content-based Student Engagement: Using Synthetic Datasets for Tableau Learning
Shane Schartz, Fort Hays State University

5:30 p.m. – 7:00 p.m.	Sequoia - Exhibit Hall

FBD Presidential Welcome Reception

All registered participants and paid guests are invited to the FBD President's Reception in the Exhibit Hall to network with colleagues and exhibitors while enjoying drinks and appetizers. Alcoholic drinks will be available through drink tickets or cash bar. Please note that in order to enter the FBD President's Reception, **everyone** must be wearing the FBD name badge received upon registration. **Name badges must be picked up before 4:30 pm on Thursday, March 20.**

Enjoy your evening in Tulsa!

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

March 21, 2025
(Friday)

7:30 a.m. – 8:30 a.m.	Council Oak A

Coffee and Conversation with ABIS and ABC–SWUS

We invite ABC-SWUS and ABIS Associations presenters and members to enjoy breakfast together!

ABC-SWUS or ABIS Association Name Badge Required for Entry

8:30 a.m. – 10:00 a.m.	Council Oak B

SESSION E **ABIS Business Meeting** *** All Members Welcome ***

Session Chairs/ABIS President: Kimberly Merritt, Oklahoma Christian University

All members are invited to join us for our annual business meeting.

10:00 a.m. – 10:30 a.m.	Sequoia - Exhibit Hall

FBD Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

10:30 a.m. – 11:45 a.m.	Council Oak B

SESSION F **Contemporary Topics in Information Systems**

Session Chair: **Michael S. Raisinghani,** Texas Women's University

#GameOver or #OverGamed? – The Effect of Self-Control and Video Gaming Addiction on Academic Stress
Kashif Saeed, University of North Texas
James Parrish, University of North Texas
Audesh Paswan, University of North Texas
Dan J. Kim, University of North Texas
Eui Jun Jeong, Konkuk University

Technology Scouting and the Role of Social Media: Leveraging Online Platforms for Innovation and Market Insights
Mahesh S. Raisinghani, Texas Women's University
Nafisa Bhuiyan, Texas Women's University
Azarria Childress-Gaynor, Texas Women's University
Neilequelette Roy, Texas Women's University

Towards Data Mining Time Management Data to Predict Student Success During COVID-19
Peter Yu, Louisiana School for Math, Science, and the Arts
Jason W. Powell, Northwestern State University
Lily Pharris, The University of Tennessee at Martin
Marcia Hardy, Northwestern State University

Digital Business Communication in the Arabian Gulf
Lamar Reinsch, Georgetown University
Jeanine Turner, Georgetown University

March 21, 2025
(Friday)

12:00 p.m. – 1:30 p.m. **Lunch on you own**

Enjoy local cuisine in Tulsa!

1:30 p.m. – 3:00 p.m. Council Oak B

SESSION G **Information Systems: Tips, Tools, and Techniques**

Session Chair: **Jason W. Powell,** Northwestern State University

Examining GMetrix Objectives in Relation to the Microsoft Office Specialist (MOS) Certification in Excel Performance in Business Courses
Nesrin Bakir, Illinois State University
Leslie Ramos Salazar, West Texas A&M University

Soft Skills in Information Systems: The Need to Develop Communication Skills
Carol S. Wright, Stephen F. Austin State University

User Review in Open-Source Software Development: Do the Developers care?
Sarif Bhuiyan, University of Central Arkansas
Kaye McKinzie, University of Central Arkansas

A Strategic Business Communication Class Partnership with The Kansas Land Institute Shaping the Institute's Website Resulting in Preparing Students in Writing Skills for the Workforce
James "Skip" Ward, Fort Hays State University

3:00 p.m. - 3:30 p.m. Sequoia - Exhibit Hall

FBC Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

3:30 p.m. - 5:00 p.m. Council Oak B

SESSION H **Multidisciplinary Perspectives Regarding (Generative) AI**

Session Chairs: **Kimberly L. Merritt**, Oklahoma Christian University

From Coordination to Collaboration: Leveraging Culture and Technology for Improved Project Team Learning
Mingyu Zhang, Florida Memorial University
Shekhar Rathor, Sam Houston State University
Weidong Xia, Florida International University

Identifying the Effectiveness of Digital Platform Based Training in the Workplace: Relationships among Training Evaluation Criteria
Suhyung Lee, Stephen F. Austin State University

Psychological, Behavioral, and Environmental Factors That Shape Cybersecurity Habits
David Horton, Northwestern State University

3:30 p.m. - 5:00 p.m. – continued Council Oak B

Leveraging LMS for Improved Student Retention: A Pedagogical Perspective A Pedagogical Perspective

Nabin Sapkota, Northwestern State University
Marcia Hardy, Northwestern State University
Susan Campbell, Northwestern State University
Mary Fair, Northwestern State University

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Please make plans to join us in Dallas/Richardson for our 2026 conference.

March 18 - 21, 2026
Renaissance Dallas Richardson Hotel, Richardson, Texas

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FROM COORDINATION TO COLLABORATION: LEVERAGING CULTURE AND TECHNOLOGY FOR IMPROVED PROJECT TEAM LEARNING

Mingyu Zhang, Florida Memorial University
Shekhar Rathor, Sam Houston State University
Weidong Xia, Florida International University

ABSTRACT

Information systems development (ISD) projects are challenging due to managing multiple stakeholders across different domains and cultures. However, over the last two decades, companies have increasingly moved towards a collaborative model in which the client and vendor share common strategic values and are mutually dependent. Collaboration is recognized as important but remains complex and challenging, with varying levels of investment and outcomes. Effective ISD collaboration plays a significant role in improving team learning. Organizations have explored a variety of practices to improve ISD collaboration and its emerging outcomes. This study examines the relationship between key collaboration facilitators in client-vendor information ISD projects and their impact on team learning. Specifically, it investigates how coordination technology, collaborative culture, and joint action interact to influence ISD collaboration and team-learning outcomes. A contextual model was developed to explain when and how effective client-vendor collaboration occurs, highlighting the crucial role of collaboration in promoting team learning. This study indicates that the use of coordination technology and the development of a collaborative culture have a significant impact on joint action and overall collaboration. This work contributes to the IT project management literature and provides practical recommendations for leveraging technology and cultural context to enhance team learning and improve IT project performance through effective collaboration.

INTRODUCTION

Information systems development (ISD) projects have become increasingly complex, involving higher-value activities, such as project planning, process design, requirements determination, and logical and physical system designs (Ko et al., 2019). In addition, effective relationship management is critical in today's economy, where project outcomes are highly dynamic and reliant on client-vendor collaboration (Stump & Heide, 1996). This paper explores how client-vendor collaboration, facilitated by coordination technologies, enhances team learning in ISD projects.

Collaboration is essential in ISD projects to address unexpected issues that cannot be managed through formal controls and plays a crucial role in promoting team learning. In addition, product development, particularly ISD collaboration, requires superior collaboration because of its functional nature (Bendoly et al., 2012; Ko et al., 2019; Mathrani & Edwards, 2020). To enhance collaborative capabilities and processes, IS vendors have implemented various communication and coordination technologies. However, ISD collaboration is challenging due to the management of multiple stakeholders with conflicting interests across different domains and cultures.

Information technology has revolutionized how organizations facilitate interaction and collaboration among group members and stakeholders who execute operational and strategic business processes (Bala et al., 2017; Lawson et al., 2009). Despite the recognized importance of collaboration, little research has focused on how specific technologies and cultural practices within client-vendor relationships directly influence team learning outcomes. Effective collaboration in ISD projects can significantly contribute to team learning. By leveraging technology and promoting a collaborative culture, organizations can enhance their collaboration capabilities, leading to better team learning outcomes and improved ISD project coordination.

Effective coordination is crucial for facilitating team collaboration and enhancing team learning in ISD projects. To achieve effective coordination, teams must develop and agree upon a common task-related goal structure with clear sub-goals and no gaps or overlaps (Hoegl & Gemuenden, 2001). Information technology plays a critical role in enabling and supporting this common task-related goal structure. Coordination technology is often implemented to facilitate collaboration among clients, vendors, and end users in ISD projects, reducing the high coordination cost associated with IT project collaboration. Many project teams prefer to coordinate their project procedures through information technology to enhance development support and engage in client-vendor collaboration.

ISD projects often face high failure rates due to miscommunication, misalignment of goals, and coordination challenges. This study focuses on collaboration and learning in a timely manner, given the industry's increasing reliance on cross-functional teams and globalized outsourcing arrangements. Research has shown that tools and techniques can significantly impact project management, including enhancing team learning (Guinan et al., 1998; Williams et al., 2011). However, despite the advancements in coordination technologies, the role of collaboration and learning in reducing ISD project failure rates remains underexamined (Bala et al., 2017). Therefore, project teams must leverage coordination technology to enhance collaboration and promote team learning in ISD projects.

While ISD outsourcing continues to grow, it is not without its challenges. Contract-based business models have contributed to high failure rates, and many uncertainties associated with ISD project activities make it difficult to specify the precise terms of the contract (Ditmore, 2019; Ko et al., 2019). This requires greater project coordination and control to ensure team member performance, which cannot rely solely on vendor contracts (Im & Ahuja, 2023; Ko et al., 2019). In addition, transforming from a short-term contract-based to a long-term collaborative-based business model requires investment in resources and changes in culture and support (Leidner & Kayworth, 2006; Smircich, 1983).

To address these challenges, many ISD vendors have shifted to collaborative development models that emphasize collaborative cultural values. A collaborative culture is essential to ISD project collaboration because it can shape how the ISD team approaches development and encourages team learning (Rai et al., 2009). It is a multifaceted value system that cannot be considered a completely isolated process from its context without any historical imprints (Le Breton-Miller & Miller, 2015; Strode, 2015; Sydow et al., 2009). The project team's cultural context plays a vital role in determining project team performance and team learning outcomes (Klimkeit, 2013; Newhouse et al., 2013; Van der Smissen et al., 2014). Collaborative culture assumes that the environment can best be managed through teamwork and employee development, the client is best thought of as a partner, the organization is in the business of developing a collaborative work environment, and the primary task of management is to empower and facilitate participation, commitment, and loyalty, ultimately leading to improved team learning (Cameron & Quinn, 2005).

Client-vendor collaboration can generate tensions that impede interactions and learning, resulting in increased distrust and promoting a distinct separation of responsibilities (Sundaramurthy & Lewis, 2003). Consequently, understanding the relationship between the collaboration context, joint action, and ISD team learning is essential. To address this, this study emphasizes the significance of team learning in the context of ISD project collaboration. This study investigates how client-vendor collaboration, supported by modern coordination technologies, impacts team learning in ISD projects and aims to identify the cultural factors that contribute to or hinder this process.

LITERATURE REVIEW

Environmental context and its collaborative effect—joint action

The success of client-vendor collaboration depends on the development of a cooperative working environment in which both parties display mutual respect and a high degree of management involvement rather than trying to dominate each other (Hoegl & Wagner, 2005; Narayanan et al., 2015). Furthermore, as the business environment becomes more dynamic and fast-changing, traditional plan-driven project development cycles become less effective, and continual collaboration with clients becomes necessary to incorporate new market conditions and requirements. Brainstorming and problem-solving sessions in ISD collaboration can lead to innovative solutions that may not have been possible if the team members had worked independently. Therefore, emphasizing team learning in ISD projects can enhance collaboration and ultimately lead to better project outcomes.

Collaborative relationships have become increasingly common since the 1980s as clients rely more on IT vendors to execute critical tasks (Gulati et al., 2012). However, traditional project management practices, such as project control, hierarchy, and formal roles, are less effective in these collaborative relationships (Lakhani et al., 2012). Thus, there is a need to reevaluate these project management logics. These practices, which are external or technological management logic outside of the development team's formal managerial practices, are referred to as project context.

This research focuses on two major project contexts: collaborative culture and coordination technology. Collaborative culture refers to the development of a cooperative working environment that promotes mutual respect and a high degree of management involvement. Coordination technology refers to the use of technology to support collaborative work, such as project management software, communication tools, and collaboration platforms.

Joint action

The success of collaboration between a client and vendor in the ISD process is determined by the joint action of the two parties. Joint action refers to the extent to which vendor and client teams work together in product design and development. It represents the interaction patterns of the two parties and extends Heide's concept of joint action - the degree of interpenetration of organizational boundaries (Heide & John, 1990). Joint action can occur during various activities, including IS design, testing, and quality control (Sabherwal, 2003; Strode et al., 2012). It is a perspective of collaboration that represents the behavioral causes of various interpersonal task relations, ranging from highly cooperative to highly uncooperative (Gulati et al., 2012).

In the ISD context, joint action allows the client and vendor to work together to develop and test new product designs and technological solutions. The two parties need to carry out major project activities in a cooperative or coordinated manner, where the boundaries of the two parties have been penetrated by the integration of activities (Heide & John, 1990). This means that the client becomes involved in activities that are traditionally considered the vendor's responsibility and vice versa (Heide & John, 1990).

Environmental context--collaborative culture

A collaborative culture is a cultural context that prioritizes and encourages collaboration, teamwork, and stakeholder cooperation. It has a significant positive impact on client-vendor collaboration in ISD projects, as both parties are more likely to work together effectively and achieve the desired project outcomes. A collaborative culture fosters open communication, employee empowerment, and participative decision-making. It encourages a team-based approach to problem-solving, in which both parties can work together to find solutions to issues that may arise during the project (Mao et al., 2008). This type of culture leads to increased innovation, improved problem-solving, and higher employee morale and job satisfaction (Cameron & Quinn, 2005).

Previous research has found that cultural context plays a vital role in project collaboration, quality, and performance (Cartaxo & Godinho, 2012; Hempel et al., 2012; Klimkeit, 2013; Newhouse et al., 2013; Park & Luo, 2001; Sila, 2007; Tsoukas, 1994 ; Van der Smissen et al., 2014). Cultural context influences an organization's choices and uses of work structure, work practices, and collaboration practices (Bechky, 2011; Bresman & Zellmer-Bruhn, 2013; Hempel et al., 2012; Kimberly & Evanisko, 1981; Oldham & Hackman, 1981). An organization's internal development process is embedded and connected with other developments as well as cultural and environmental characteristics (Child, 1997; March, 1994; Sydow et al., 2009). Matching an organization's competitive environment with its environmental structure is crucial for success (Venkatraman, 1990). The success of any ISD project will depend on adopting appropriate cultural characteristics sufficient to deal with relevant environmental factors (Simerly & Li, 1999; Sydow et al., 2009).

H1: The greater the degree to which the ISD vendor developed a collaborative culture in its interactions with its clients, the greater the joint action will be produced.

Technology context--coordination technology

Coordination theory explains that coordination problems arise because of unmanaged dependencies between tasks and resources in organizational activities. Coordination is defined as the process of managing dependencies between interdependent tasks and resources (Crowston, 1997; Crowston et al., 2004). This theory offers a framework for managing coordination problems in complex environments that involve multiple tasks and resources.

Previous research suggests that coordination mechanisms rely on other organizational functions such as decision-making, communication, and the development of shared understanding. Therefore, teams or organizational units must perform additional coordination tasks to manage these problems. Information Technology (IT) has been proposed as a key facilitator of coordination tasks, improving coordination and collaboration among individuals, tasks, and resources (Bala et al., 2017).

IT-enabled coordination processes are major attempts by IT vendors to assist clients' information-sharing requirements and deal with developmental uncertainties. The use of collaborative technology in ISD projects can influence the collaboration effect (Bala et al., 2017). Whereas behavioral researchers suggest that interpersonal relationships, interactions interpersonal relationships, and interactions are also critical factors in determining success (Ancona & Caldwell, 1992; Jassawalla, 2003; Smolander et al., 2016). However, no one would argue that the behavioral perspective is complete by itself (Guinan et al., 1998). To achieve a more comprehensive understanding of IT project collaboration, we must consider technological perspectives, such as coordination technology, as a major factor.

In the ISD project context, because of the remote collaboration prerequisite, the client can only evaluate the project progress at the end of each development iteration and provide feedback and new requirements based on the demonstration of the development team. Thus, within each iteration, IT development tasks and progress are neither entirely visible nor accessible to the client. This lack of task progress information can cause performance ambiguity, thereby making collaborative tasks more difficult (Heide & Miner, 1992). To better cooperate with the client, the project team needs to constantly communicate with the client to confirm the project design and coordinate project-related problems. Therefore, the implementation of remotely viable coordination technologies is critical for project collaboration.

The culture of an ISD team significantly influences project development and management practices, and a shared set of norms and values can help develop a trusting relationship between the client and the vendor (Doney et al., 1998; Mao et al., 2008). In addition, organizational culture facilitates the formation of collaborative relationships. Therefore, a collaborative culture is essential for effective project collaboration and team performance.

H2: The greater the degree to which an ISD vendor utilizes coordination technology in its interactions with clients, the greater the effect of joint action will be produced.

The success of team learning in ISD projects

In IS projects, achieving team outcomes goes beyond meeting software development and business domain objectives; it also involves promoting team learning and future teamwork capabilities (Hoegl & Gemuenden, 2001). Team learning in IS projects is crucial for fostering the professional and personal growth of team members (Denison et al., 1996). Team learning is influenced by various factors, such as the team's ability to collaborate, learn new skills, resolve conflicts, adapt to changes, and identify and mitigate risks and issues throughout the project lifecycle (Hoegl & Gemuenden, 2001). Collaboration in ISD requires team members to work together towards a common goal, often involving sharing knowledge and expertise. This sharing of information can improve team learning by enabling individuals to learn from one another and develop new skills (Hoegl & Gemuenden, 2001).

Team learning in IS projects can be further enhanced through the use of technology to facilitate coordination and knowledge-sharing. Coordination technology can provide platforms for team members to share ideas, documents, and data, leading to increased learning opportunities and faster decision-making (Hoegl & Gemuenden, 2001). By leveraging technology, team members can communicate and collaborate more effectively, leading to improved learning outcomes (Bala et al., 2017).

However, technology alone cannot facilitate team learning in IS projects. Effective team learning requires a culture that values learning and encourages knowledge-sharing (Denison et al., 1996). The project environment should support open communication and collaboration, and team members should be encouraged to ask questions, share ideas, and seek feedback from one another (Hoegl & Gemuenden, 2001). Overall, team learning is a critical component of successful IS projects and requires a combination of culture, technology, and joint effort to be effectively fostered.

H3: The greater the degree to which the ISD vendor develops a collaborative culture in its interactions with its clients, the greater the effect of team learning will be improved.

H4: The greater the degree to which an ISD vendor utilizes coordination technology in its interactions with clients, the greater the effect of team learning will be improved.

H5: Higher levels of joint action between client and vendor led to better effect of team learning.

Tensions and reinforcing processes of collaboration-- client's formal control

Client-vendor collaboration is essential for successful ISD projects, but it requires alignment between the two parties and the resolution of paradoxical tensions between collaboration and control. However, they can become trapped within reinforcing mechanisms that intensify a client's control needs. These mechanisms can be a double-edged sword, as emphasizing one polarity can exacerbate the need for the other, leading to defenses, hindering learning, and triggering counterproductive control cycles (Sundaramurthy & Lewis, 2003). To fully capture the multidimensional concept of client control, two separate mechanisms should be examined: outcome controls and behavior controls. The use of these mechanisms can help to reflect the complexity of control in a sufficient manner (Langfield-Smith & Smith, 2003).

As ISD teams can differ in their cultures, management styles, and collaboration intentions, the process of management alignment often involves incorporating more of the client's management style into the development process (Sarangi & Slembrouck, 2014). By understanding the client's control mechanisms, the two parties can work together more effectively toward achieving agreed-upon objectives (Sarangi & Slembrouck, 2014). Control can be viewed as a means by which clients attempt to ensure that individuals working on organizational projects act according to an agreed-upon strategy to achieve the desired outcomes (Berry et al., 2009; Rustagi et al., 2008). Therefore, understanding a client's control mechanisms is crucial for successful collaboration between the client and vendor.

H5A: The effect of joint action on team learning improvement in ISD projects is moderated by a client's formal control.

RESEARCH MODEL AND METHODOLOGY

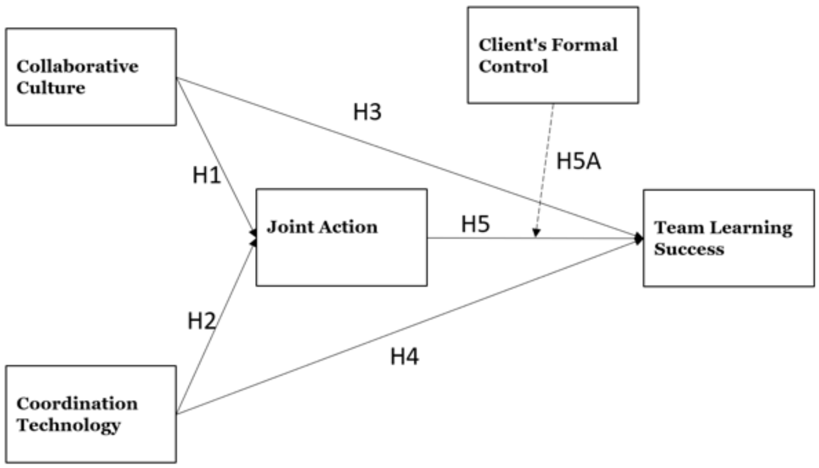

Figure 1: Research model with hypotheses

This study uses quantitative methods to test the hypotheses. The data will be collected using an online survey. IT professionals (software developers, testers, business analysts, managers) working on ISD project will be the respondents. Respondents will be approached by contacting IT companies in India, China, and the US, and the survey will be linked to relevant groups on LinkedIn. The data will be analyzed using the PLS-SEM statistical technique.

Our research design followed a four-phase process (Xia & Lee, 2003): (1) conceptual development and initial item generation, (2) conceptual refinement and item modification, (3) survey data collection, and (4) data analysis, measurement validation, and research model testing.

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EXAMINING GMETRIX OBJECTIVES IN RELATION TO THE MICROSOFT OFFICE (MOS) CERTIFICATION IN EXCEL PERFORMANCE IN BUSINESS COURSES

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ABSTRACT

Microsoft Excel continues to be the most popular software to teach business courses. Employers continue to expect undergraduate students to have proficiency in various functions of Microsoft Excel. When students become certified in software applications, employers perceive students to be quality employee candidates. In this study, the GMetrix objectives, which train and test students on various features of Microsoft Excel, were used to determine whether they predicted higher scores on the Microsoft Office specialist (MOS) Certification exam. The sample included 224 students from two information science courses in a college of business. Multiple linear regression identified specific GMetrix objectives as significant predictors of increased MOS exam performance. Further, simple linear regression analyses demonstrated that preparedness score predicted higher MOS scores. Implications are also offered for instructors of information science and business courses.

Key words: *Microsoft Office Specialist, Excel, Certification, Exam Performance, Business Courses*

INTRODUCTION

Technological literacy is crucial for employability and staying competitive in today's economy. Employability is defined as "an individual's chance of a job on the internal and/or external labor market" (Forrier & Sels, 2003, p. 106). For business graduates, data analytics knowledge and skills to solve business problems has increased significantly in recent years (Cainas et al., 2021). As a result, the knowledge and skills of Microsoft Excel in business programs becomes essential. Microsoft Excel continues to be the most popular and demanded data analytics software and productivity tool (Agnese, 2024; Bingi et al., 2013; Cory & Pruske, 2012; Rose et al., 2021). Reddy (2022) outlined a list of essential Excel skills that employers seek in business graduates. Some of these skills include functions and calculations, data sorting, validation, and analysis, graphing and charts, and formatting. Microsoft Office specialist (MOS) Certification issued by Microsoft, measures these skills which prepares students with basic and advanced Excel skills to be successful in the job market. MOS in Excel tests students in five areas: a) manage worksheets and workbooks, b) manage data cells and ranges, c) manage tables and table data, d) perform operations by using formulas and functions, and e) manage charts. One approach to prepare students for the MOS exam is with GMetrix (2024), a web-based system. This performance-based software offers two modes: training and testing. In training mode, students receive step-by-step help on each question without any time constraints, whereas testing mode simulates the real certification exams with timed practice.

The purpose of this study is to examine the relationship between students' individual GMetrix scores and their performance on the MOS exam in undergraduate information science courses.

This study is important because examining the predictive value of GMetrix scores can help identify how well these scores can forecast students' success on the MOS exam. The findings will provide guidance to educators who are interested in implementing the MOS certification and the effectiveness of GMetrix in the preparation of their students for the MOS exam.
The study addressed the following research question: How do students' individual GMetrix scores predict their performance on the MOS exam in information science courses?

LITERATURE REVIEW

Importance of Certification Exams in IS Career Development

Certifications among information systems students have become important in their career development. Certifications greatly impact employability (Carnevale et al., 2012) and marketability (Call, 2017; Foster & Pritz, 2006). The 2019 Pearson VUE Value of IT Certification survey revealed that employees gained advantages from earning a certification. Specifically, 65% reported an improvement in their professional image, 35% received a salary raise, 28% took on new job responsibilities, and 26% were promoted. Randall and Zirkle (2005) define entry-level certifications as a "vehicle to provide students with viable skills needed by the workforce, to satisfy state skill standards, and to prepare students for postsecondary studies" (p. 287). Ray and McCoy (2000) argued that the benefits of certification exams for students include being perceived as valuable and skillful to employers in being up-to-date with the latest software technologies. They further argued that employers also benefit from hiring certified students because it guides them in hiring quality job candidates and in assessing their capabilities. Further, a national study found that information systems certification exams resulted in an increase of salary of 14% in comparison to those without certification (DataMasters Business Solutions, 2000). Additionally, some employers may require software certification exams as proof of knowledge of computer skills such as Microsoft Excel and C+ (Hitchcock, 2007). "Certifications act as a signal to hiring managers that a job candidate has achieved a level of knowledge and skill necessary to perform in a particular IT job role" (Randall & Zirkle, 2005, p. 290). For example, Wiershem et al. (2010) found that of the 141 employers in the information technology field, 45% mandated or preferred that their employees have IT related certifications. As a result, there has been a demand for certification exams among newly graduated graduates and in the need to incorporate them into the information science curriculum (Rob, 2014).

Importance of Certification Exams in Information Systems Curriculum

In a survey study, Rob and Roy (2013) examined IT certifications including Microsoft software certifications in their graduate MIS curriculum at the University of Houston-Clear Lake among 70 students and found that students believed IT certification exams helped them to enhance their IT career opportunities. Around 67% of middle-skill job openings require at least basic proficiency in productivity software (Rose et al., 2021). According to Tarver et al. (2009), 67.5% of participants felt they benefited from obtaining the MOS certifications, and 56% indicated that the certifications helped them secure employment. However, 32% of the participants reported no perceived benefit. Bahr and Booth (2012) also found a 30% increase in wages for those who had certificates. Further, Hunsinger and Smith (2008) examined the factors that would predict undergraduate information systems students in completing IT certification such as Microsoft

Certified Professional and Cisco Certified Network Associate using the theory of planned behavior among 120 students. Based on their results, students' attitude, subjective norm, perceived behavioral control, cognition, and affect positively related to pursuing IT certification. Further, students had positive attitudes about pursuing IT certification such as increasing their ability to get hired and compete with other candidates in IS careers.

Another study integrated IT certification goals into an information system course. In their study, Al-Rawi and colleagues (2006b) examined CompTIA A+ objectives through exams, and they related these to the course. Their exam objectives included core hardware (i.e., installation, diagnosing, preventative maintenance) and operating system technologies (i.e., OS fundamentals, diagnosing, networks). Findings from the application included needing 70 hours of course implementation, covering objectives areas in courses in IS curriculum, and requiring certification exams as part of the assessment in the syllabus (Al-Rawi et al., 2006b). In a review study, Al-Rawi et al. (2006a) explained that certifications such as MOS can enhance students' personal productivity in using technology. In using the MOS, students can learn important Excel skills, and the authors recommend incorporating certification exams in undergraduate courses.

METHODOLOGY

Participants

Participants included undergraduate students enrolled in two College of Business courses at a regional university in the Southern part of the U.S. Out of 261 students, 224 participated in the study with a response rate of 86%. There were more male students (54%) than female students (46%). Thirty-eight percent of the participants were juniors followed by seniors (26%), sophomores (24%), and freshmen (13%). Their age ranged from 17-40 (M=21.19, SD =. 3.27). Participants were enrolled in a variety of majors. The majority of the students (78%) majored in business and the remaining (22%) were non-business majors. The business majors included computer information systems, accounting, management, general business, finance, marketing, and economics. The non-majors included education, social work, psychology, art, dance, criminal justice, general studies, health/sport/animal science, communication, Spanish, history/art history, engineering, and graphic design.

Context

The study took place in an introductory university information science core course and a required Management of Information systems course for all business students. Both courses were three-credit hours, focused on Microsoft Office Excel, and met face-to-face during a 16-week semester. GMetrix was used to prepare students for the MOS exam and to familiarize them with the testing software. The MOS training lasted 10 class sessions which included instructor-led demonstrations, and custom-created GMetrix learning activities, and reviews of weekly GMetrix assignments with students in the training mode. Participants were required to complete four GMetrix assignments with a minimum score of 95% or higher in the testing mode prior to taking the exam. Each GMetrix assignment was custom designed based on the MOS objectives (See Table 1) and mirrored an actual exam.

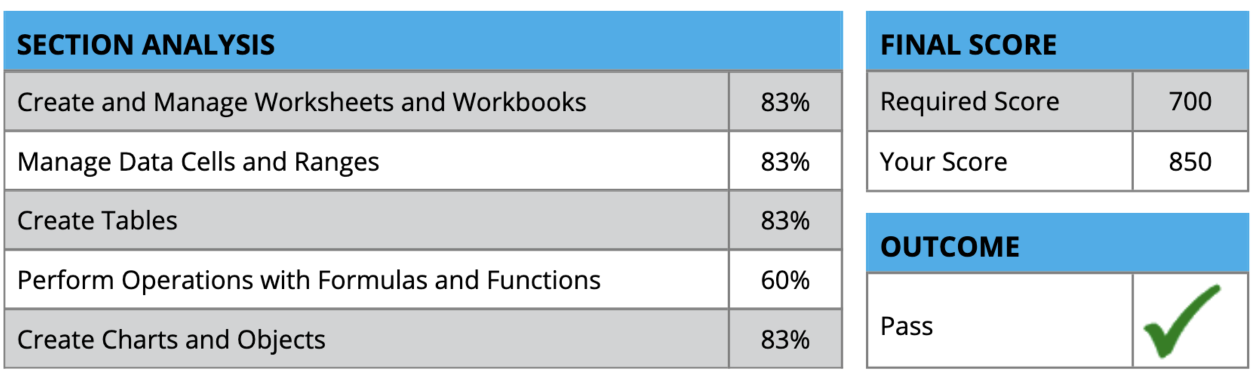
Table 1. MOS and GMetrix Objectives

MOS and GMetrix Objectives
Objective 1: Create and Manage Worksheets and Workbooks
Objective 2: Manage Data Cells and Ranges
Objective 3: Create Tables
Objective 4: Perform Operations with Formulas and Functions
Objective 5: Create Charts and Objects

Data sources and analysis

Data came from students' Microsoft Office Specialist exam scores and four GMetrix assignment scores. A survey was also given at the beginning of the semester to students to collect basic demographic variables such as course enrolled, gender, age, academic level, and major. At the completion of the MOS exam, each student received an exam score report from Microsoft (See Figure 1). The report included a percentage analysis of how each student did in each objective area. GMetrix also provided a similar report for each of the required assignments.

Data analysis included multiple linear regression and simple linear regression. Analytical assumptions were checked to ensure linearity and multicollinearity issues were not a concern. These data analyses were conducted using SPSS.



SECTION ANALYSIS	
Create and Manage Worksheets and Workbooks	83%
Manage Data Cells and Ranges	83%
Create Tables	83%
Perform Operations with Formulas and Functions	60%
Create Charts and Objects	83%

FINAL SCORE	
Required Score	700
Your Score	850

OUTCOME	
Pass	✓

Figure 1. Example of MOS Exam Score Report

RESULTS

The purpose of this study is to examine the relationship between students' individual GMetrix scores and their performance on the MOS exam. A multiple linear regression was used to examine whether GMetrix scores predicted MOS exam scores. All twenty GMetrix objective combinations were entered into the analysis. Table 2 reports the results. The only GMetrix score to predict MOS exam performance was GMetrix3 for Objective 5. Controlling for all other scores, for every one-unit increase in the GMetrix3 score on Objective 5, there was a 1.61-point increase in MOS exam scores ($p < .05$).

Table 2. Effects of GMetrix Scores on MOS Exam Performance

	Unstandardized Coefficients		
	β	SE	Sig.
(Constant)	578.166	64.787	.000
GMetrix1 Objective1	-1.058	1.256	.401
GMetrix1 Objective2	-1.930	1.212	.113
GMetrix1 Objective3	1.925	1.339	.152
GMetrix1 Objective4	-.598	.715	.404
GMetrix1 Objective5	2.101	1.464	.153
GMetrix2 Objective1	-1.796	1.654	.279
GMetrix2 Objective2	.530	1.114	.634
GMetrix2 Objective3	-.428	1.681	.799
GMetrix2 Objective4	2.014	1.214	.099
GMetrix2 Objective5	-.666	1.181	.573
GMetrix3 Objective1	-.604	1.271	.635
GMetrix3 Objective2	.169	1.086	.877
GMetrix3 Objective3	1.099	1.283	.393
GMetrix3 Objective4	-.854	1.047	.415
GMetrix3 Objective5	1.613	.781	*.040
GMetrix4 Objective1	.169	1.146	.883
GMetrix4 Objective2	.556	1.403	.692
GMetrix4 Objective3	-1.774	1.180	.134
GMetrix4 Objective4	-.010	.728	.989
GMetrix4 Objective5	1.804	1.014	.077

*$p < .05$ **$p < .001$

Multiple linear regressions were then run separately to look at the effects of each of the five GMetrix scores on MOS exam scores. Objective 3 was the only one under GMetrix 1 to predict higher exam scores. For every point increase in the GMetrix1, Objective 3 score there was a 2.77 point increase in the MOS exam score ($p < .05$). Table 3 presents the full results for the regression analysis.

Table 3. Effects of GMetrix1 Scores on MOS Exam Performance

	Unstandardized Coefficients		
	β	Std Error	Sig.
(Constant)	590.148	54.787	.000
GMetrix1 Objective1	-.947	1.220	.439
GMetrix1 Objective2	-1.664	1.163	.154
GMetrix1 Objective3	2.768	1.233	*.026
GMetrix1 Objective4	.406	.673	.547
GMetrix1 Objective5	1.429	1.415	.314

*$p < .05$ **$p < .001$

Table 4 presents results of the regression analysis for GMetrix2 scores. GMetrix2, Objective 4 was the only significant predictor of MOS exam performance. Controlling for all other GMetrix scores, for every one-unit increase in GMetrix2, Objective 4 score, there was a 2.67-point increase in MOS exam scores ($p < .05$).

Table 4. Effects of GMetrix2 Scores on MOS Exam Performance

	Unstandardized Coefficients		
	β	SE	Sig.
(Constant)	599.643	58.322	.000
GMetrix2 Objective1	-.016	1.576	.992
GMetrix2 Objective2	.894	1.034	.388
GMetrix2 Objective3	-1.307	1.551	.400
GMetrix2 Objective4	2.673	1.134	*.019
GMetrix2 Objective5	-.293	1.110	.792

*$p < .05$ **$p <.001$

Table 5 presents the results of the regression analysis examining the effects of GMetrix3 scores on MOS exam performance. GMetrix3, Objective 5 was the only significant predictor of MOS exam performance (as it was in the regression with all GMetrix scores, see Table 2). Controlling for all other GMetrix scores, for every one-unit increase in the GMetrix3, Objective 5 score there was a 1.79-point increase on the MOS exam ($p < .05$).

Table 5. Effects of GMetrix3 Scores on MOS Exam Performance

	Unstandardized Coefficients		
	β	SE	Sig.
(Constant)	618.238	44.852	.000
GMetrix3 Objective1	-1.383	1.199	.250
GMetrix3 Objective2	.178	1.045	.865
GMetrix3 Objective3	1.507	1.209	.214
GMetrix3 Objective4	-.192	.964	.842
GMetrix3 Objective5	1.791	.705	*.012

*$p < .05$ **$p <.001$

Table 6 presents the results of the regression analysis for GMetrix4 scores. GMetrix4, Objective 5 was the only significant predictor of MOS exam performance. Controlling for all other GMetrix scores, for every one-unit increase in the GMetrix4, Objective 5 score there was a 2.22-point increase on the MOS exam (β=.44, $p < .05$).

Table 6. Effects of GMetrix4 Scores on MOS Exam Performance

	Unstandardized Coefficients		
	β	SE	Sig.
(Constant)	681.822	30.977	.000
GMetrix4 Objective1	-.143	1.115	.898
GMetrix4 Objective2	-.016	1.302	.990
GMetrix4 Objective3	-1.294	1.163	.267
GMetrix4 Objective4	.357	.708	.615

GMetrix4 Objective5	2.216	.940	*.019

*$p < .05$ **$p <.001$

Perceived preparedness scores were then entered into four separate simple linear regression analyses to examine if preparedness scores predicted each GMetrix score. The results were significant for GMetrix1. For every one-unit increase in perceived preparedness, there was a 6.39-point increase in the GMetrix1 score (p < .01). Perceived preparedness did not have an effect on GMetrix2 scores ($b = 3.095$, $t(224) = 3.095$, $p > .05$). The next two regressions showed preparedness scores had a significant effect on GMetrix 3 score ($b = 6.44$, $t(224) = 2.416$, $p < .001$), but not the GMetrix 4 score ($b = 4.53$, $t(224) = 1.23$, $p > .05$). A one-point increase in the preparedness score predicted a 6.44 increase in the GMetrix 3 score.

Finally, the preparedness score was entered into a simple linear regression with MOS score. The results indicated that for every one point increase in the preparedness score, the MOS score increased by 92.14 points ($b = 92.14$, $t(224) = 4.743$, $p < .001$).

DISCUSSION

The purpose of this study was to examine students' GMetrix scores as a predictor of their performance on their MOS exam in information science courses. Twenty GMetrix objective combinations were entered into the same regression model to determine their effects on MOS exam scores. One important finding was that GMetrix1 (Objective 3) involving managing tables and table data was a positive predictor of exam performance. This finding is consistent with Khan's (2019) work in finding that students' Excel skills in relation to developing table outputs when engaging in data mining is positively correlated with students' course and assignment performance. When students are able to create tables from data sets, this skill enables them to perform better on exams.

Additionally, this study found that GMetrix2 (Objective 4) focusing on performing operations by using formulas and functions also predicted students' exam performance. This finding is consistent with prior research by Iji and colleagues (2022) that when secondary school students are prepared with Excel spreadsheet technology including calculating formulas and functions, students are more academically successful in mathematics courses than those without that preparation. Gil (2022) also found similar results using a finance course at a Mexican university. Students with Excel function and formula skills performed better on exams than students without such skills. This finding reinforces previous research by confirming its applicability within information science courses.

Further, GMetrix3 (Objective 5) and GMetrix4 (Objective 5) assessed students' ability in creating charts and objectives, which played a crucial role in their success on the MOS exam. Specifically, doing well on Objective 5 predicted higher MOS scores in two of the four separate analyses. It might be that the GMetrix tests better prepared students to do well on Objective 5 on the MOS. Past research has found that students' performance in creating charts and graphs such as pie and bar charts using Microsoft Excel (experimental group) is positively related to their academic performance in comparison to those who cannot create visuals with Microsoft Excel

(control group) (Nchelem & Seyram, 2021). However, the finding from this study contributes to this work by demonstrating a link to MOS exam performance.
An important contribution of this study was that students' perceived preparedness scores did predict higher scores on GMetrix1 (creating and managing worksheets and workbooks) and GMetrix3 (creating tables) as well as on the MOS exam. This indicates that when students felt better prepared for their exams, they generally did better. It might be worth making sure that students feel they are well prepared for the skill sets under GMetrix2 (managing data cells and ranges) and GMetrix4 (performing operations with formulas and functions) since feeling prepared did not necessarily translate to better performance in those GMetrix exams. However, perceived preparedness was a general predictor of students' MOS score, such that prepared students did better than those who felt less prepared. A prior study found that students' perceived preparation from training for exams and preparing for seminars can improve students' exam and course performance because of their increased self-belief and motivation in doing well in assessments (Bouwmeester et al., 2016). Further, courses that use technological tools to prepare students can increase students' feelings of preparation have also been shown to improve students' performance and engagement in business courses (Francescucci et al., 2021). Also, students who do not feel prepared have low performance expectations of themselves, and are likely to experience higher levels of anxiety than those who feel prepared, which explain their reduced exam performance (Burns, 2004).

IMPLICATIONS

Several implications are derived from this study. Several GMetrix objectives are positively related to MOS exam scores, which suggest that students who are assessed with GMetrix may be more likely to score higher on their MOS exam. Particularly, GMetrix1's measurement of managing tables and table data helped students to develop tables with Microsoft Excel. Also, GMetrix2's measurement of using Excel formulas and functions enabled students to feel comfortable with Excel. Further, GMetrix3 and 4's measurement of managing charts enabled students to develop visualization charts using Microsoft Excel. Because students became familiar with various features of Excel using the GMetrix objectives, students were able to increase their MOS exam scores in the certification process.

Instructors of business information systems courses may adopt GMetrix's objectives within their IS courses and syllabi to help students enhance their MOS exam performance and improve certification success rates. Instructors may incorporate GMetrix graded activities throughout the semester and include the MOS certification as part of their graded criteria. As a result, students may benefit by receiving specific training and being able to demonstrate their knowledge through completing the MOS exam.

Administrators may also encourage instructors to adopt GMetrix objectives training and MOS certification as part of their information systems curriculum to ensure IS students are hirable upon graduation at the undergraduate levels. Further, by increasing the MOS certification among undergraduate students, it can help fulfill AACSB accreditation standards. The reputation of IS departments may also be increased by increasing the social media stories involving the certification of their students.

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USER REVIEW IN OPEN-SOURCE SOFTWARE DEVELOPMENT: DO THE DEVELOPERS CARE?

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ABSTRACT

Open-source software projects are routinely reviewed and rated by users. Researchers have looked at various motivations that can lead to participation in open-source software projects. However, the existing research does not include an examination of the relationship between user reviews and continued voluntary participation in open-source software development. Continued voluntary participation is so fundamental to the development of open-source software that any factor that can potentially impact participation must be examined. Using a 2 (volume) × 2 (valence) experimental design, this study examines the potential influence of user review on the intention to continue to participate in open-source software projects.

STRATEGIC INFORMATION SYSTEMS: INTEGRATING QUALITY MANAGEMENT 4.0 WITH AI AND MACHINE LEARNING

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ABSTRACT

This manuscript develops a novel framework of integrating Quality 4.0 principles to strategic planning processes, based on the review and synthesis of recent literature on project quality management, Quality 4.0, and strategic planning. While strategic planning remains critical for shaping organizational objectives, there is limited research on leveraging quality management practices in this context. The methodology involves a qualitative literature review, outlining quality management evolution and discussing Quality 4.0's use of AI and machine learning. Gaps are identified regarding integrating quality with strategic planning processes. A novel framework is proposed for "Strategic Planning 4.0" that incorporates Quality 4.0 principles of automation, data analytics and machine learning into the strategic planning process. Implications for enhancing strategic planning through Quality 4.0, limitations, and areas for future research are discussed, positioning organizations for success in the Industry 4.0 era.

TECHNOLOGY SCOUTING AND THE ROLE OF SOCIAL MEDIA: LEVERAGING ONLINE PLATFORMS FOR INNOVATION AND MARKET INSIGHTS

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ABSTRACT

This paper explores how social media platforms serve as crucial tools for technology scouting, enabling organizations to identify emerging innovations and market trends. Technology scouting, a strategic process of discovering and assessing new technologies, has been significantly enhanced by social media's vast data resources and real-time interactions. Platforms such as Twitter, LinkedIn, and Reddit facilitate trend monitoring, professional insights, and grassroots discussions, offering companies valuable intelligence on technological advancements.
The study highlights successful case studies where organizations have leveraged social media for technology scouting. Examples include IBM Watson Health's use of Twitter to track AI applications in healthcare, Ford's reliance on LinkedIn to assess electric vehicle trends, and Amazon's analysis of Reddit discussions to refine its drone delivery strategy. These cases demonstrate the tangible benefits of integrating social media insights into innovation and investment decisions.

Furthermore, the paper discusses strategies for effective technology communication and dissemination through social media. Key tactics include using clear and engaging content, leveraging influencer marketing, and fostering online communities for collaborative knowledge-sharing. Social media influencers play an increasing role in shaping technological adoption, driving engagement, and enhancing brand credibility.

Challenges such as information overload, ensuring data credibility, and navigating privacy concerns are also addressed. The paper suggests that organizations employ advanced analytics, AI-driven monitoring tools, and ethical frameworks to mitigate these risks while maximizing social media's potential.

In conclusion, social media has transformed technology scouting, making it a dynamic and essential tool for staying competitive in a rapidly evolving digital landscape. Organizations that effectively harness social media insights can accelerate innovation, improve strategic decision-making, and strengthen market positioning.

AI – ALL IN?
AN ANALYSIS OF STUDENT USE AND PERCEPTIONS OF AI USAGE IN COLLEGE COURSES

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ABSTRACT

In this paper, the authors present a literature review and an examination of current online resources regarding the utilization of Artificial Intelligence (AI) by students in the college classroom. Businesses, education entities, and society assert that AI is a tool that must be integrated into the college curriculum to adequately prepare students for professional careers. However, often time specific AI tools or skillsets cannot be identified. For this initial study, the authors conducted an analysis of existing literature that explores student usage and perceptions of AI in higher education settings. Furthermore, the authors intend to perform follow-up studies, initially surveying students at their respective universities to determine usage, awareness, and opinion regarding various applications of AI in assignments and assessments, and later surveying faculty at the same universities for similar information.

Keywords: *Artificial Intelligence, AI, Higher Education, AI in Curriculum*

INTRODUCTION

While the concept of AI, Artificial Intelligence, dates back to the 1950s, it was not until the 1990s that real-world business applications such as Intelligent Agents or bots were introduced, and AI tools became a part of many business environments. The introduction of Machine Learning also provided applications such as speech recognition applications in 1997 and facial recognition software in 2002 (Foote, 2022). The introduction and enhancements of these AI tools changed the processes and policies in several businesses and industries. However, it wasn't until November 2022 when OpenAI launched ChatGPT that higher education students were introduced to an AI tool, a chatbot that could provide answers, write research papers, and so much more. While OpenAI has struggled to keep up with the necessary changes and adjustments to "*one of the most popular internet apps ever*," faculty and administration at all levels of the education system have struggled to find ways to ways to block, stop, or in some cases incorporate this AI tool into the classroom setting (Heaven, 2023).

Limited research and varied views on Artificial Intelligence in Education (AIED) exist, particularly regarding some of the newer large language model applications such as ChatGPT. Higher education administrators are struggling to find a balance with regard to AI in the classroom. In some instances, the use of AI is prohibited, administrators asserting that any use of AI is considered cheating or plagiarism. In others, several AI tools have been created for classroom environments to facilitate advanced learning experiences that typically cannot be replicated in a traditional textbook setting. In addition, many in the business community are embracing AI tools, such as ChatGPT, to help increase productivity and minimize repetitive and time-consuming tasks. They are looking for graduates with AI experience. A 2023 exploratory study by Cardon et al. agreed that business students must develop AI literacy to succeed in the workplace (Cardon, Fleischmann, Aritz, Logemann, & Heidewald, 2023).

The purpose of this paper is to begin reviewing students' perspectives on the use of AI in college classrooms. This includes applications such as ChatGPT and other AI tools either introduced by faculty or self-selected by students. Once the initial literature review is complete, the authors intend to further this study by surveying students and faculty at their respective universities.

REVIEW OF THE LITERATURE

Higher education institutions, administrators, and faculty have utilized AI tools for decades. Programs and websites that assist faculty in grading, create personalized assignments, provide immediate feedback with customized tutoring features, and offer 24/7 help for certain topics are just a few examples. The use of such tools multiplied during COVID 19 when most college classrooms switched from a traditional to an online format. Chassignol et al. state that the potential benefits of such personalized learning are numerous, with models showing reduced student dropout rates (Chassignol, Khoroshavin, Klimova, & Bilyatdinova, 2018). Djokic et al. also affirm that the use of AI is often successful in areas where students lack personal attention, understand their own specific needs, and can prompt responses to their needs (Djokic, Milićević, Djokic, Malcic, & Kalas, 2024). Many faculty and students may not think of such programs and tools as AI applications, but they are.

Asio and Gadia (2024) agree that although students are unaware of it, they are already using AI in their learning process. In the academic year 2023-24, they conducted a study of 708 participants in the Philippines to investigate the predictors of students' attitudes toward AI. The study included questions regarding the students' attitudes toward the cognitive, affective, and behavioral components of AI. Cognitive questions focused on the perceived importance of AI in the classroom and the need for education on AI for all students. Affective questions focused on AI's importance to society, making lives convenient, problem-solving in real life, and whether necessary to learn and use. Behavioral questions focused on working in an AI field, interest in the uses of AI, interest in continuing to learn more about AI, and choosing a job in an AI field. For all questions in these categories, students either agreed or moderately agreed; no question's responses were significantly different.

Additional questions in the Asio and Gadia 2024 study focused on AI literacy and self-efficacy. AI literacy questions focused on using AI every day, AI making life/ tasks easier, new and future uses of AI, ethical considerations, and the impact AI has on society. In this question set, while the majority of students' answers fell in the moderate range, students strongly agreed that they could assess the advantages and disadvantages of using AI and strongly disagreed that they could develop AI applications. Self-efficacy questions included the ability to use AI in difficult and new situations and keeping up with the latest changes and applications. Here again, most students' answers fell in the moderate range.

The final component of the Asio and Gadia 2024 study compared the students' perspectives on AI for the previously stated question areas while also considering the following: available gadgets at their home, college/department, academic level, age, and gender. Beginning with available gadgets, significant differences were also shown when comparing student responses with the available gadgets at home. Students with laptops and PCs, compared to those with only a smartphone or iPad, reported significantly higher on questions related to AI literacy and self-efficacy. Next, the study found differences in the students' attitudes toward AI when compared to both the student's college/department and academic level. This study did not find a significant difference in students' perspectives on AI between age groups. However, the study did find a significant difference when comparing gender. Differences were found in all areas of the study, including the students' attitudes toward AI, containing the cognitive, affective, and behavioral components, AI literacy, and self-efficacy. This part of the study has similar findings to a 2024 study by Stohr, Ou, and Malmstrom.

The overall findings of the Asio and Gadia 2024 study highlighted student attitudes toward AI and noted several differences in student perception of AI depending on the available gadgets in their homes, college/department, academic level, and gender. However, the introduction of ChatGPT and similar AI chatbots and tools flipped the script on higher education. While faculty have used AI tools to help in their classrooms, grading, and interaction with students, now students can use AI to generate written work, create supplemental resources, and generate ideas for projects.

A study by Stohr, Ou, and Malmstrom (2024) examined the difference in students' familiarity with, usage of, and attitude towards ChatGPT and other AI chatbots, based on gender, academic level, and field of study. The study was conducted in April – May 2023 and included 5,894 students from various Swedish universities. When asked about their usage of chatbots, 93.7% of the students were familiar with ChatGPT, with 35.4% using it regularly, and 31% being familiar with but never using it. Similarly, 40.4% were familiar with Bing AI, with only 2.3% using it regularly and 31.6% being familiar with but never using it. Regarding Microsoft CoPilot, 19.6% were familiar with it, with only 2.3% using it regularly, and 14.3% being familiar with but never using it.

Stohr, Ou, and Malmstrom's 2024 study also focused on the students' attitudes towards AI chatbots when used in education. General attitude questions revealed that the majority of students had a positive attitude toward the use of chatbots in education but were also concerned about how AI chatbots will impact students' learning in the future. When asked if chatbot usage was common among their fellow students, 40.8% reported that they did not know or preferred not to say. Looking directly at the effects of chatbots on learning and performance, while 47.7% of students reported that chatbots made them more effective learners, 44% stated that it did not improve their general language ability, 50.4% stated that it did not generate better results than they could on their own, and 40.4% stated that it did not improve their grade.

Regarding the ethical aspects of using chatbots and its implication on academic integrity, 58% of students in this same study felt that using chatbots goes against the purpose of education. However, 61.9% stated that they do use them to complete assignments and cheat on exams. While the usage of chatbots on assignments and exams was high, 60.5% of students felt that

using chatbots should be prohibited in education settings, but only 19.1% stated that their teacher or university had rules or guidelines on the responsible use of chatbots; the majority, 55%, stated that they either did not know or preferred not to say.
Stohr, Ou, and Malmstrom (2024) concluded their study of students' familiarity with, usage of, and attitude toward ChatGPT and other AI chatbots, by comparing the results based on gender, academic level, and field of study. Regarding gender, significant differences were found in the perception of AI chatbots among males and females. Female students appeared more concerned about the impact of AI on education, felt that chatbots should not be used in education, and viewed the use of chatbots on assignments and exams as cheating. Male students had an overall positive attitude toward chatbots and perceived them as tools to both improve their learning and grades. When comparisons were made between academic levels, the study identified significant differences. Swedish universities have first-, second-, and third-year students. First-year students were less familiar with chatbots, particularly with Bing AI and the lesser-known bots, and had lower reports of usage. Second-year students showed more familiarity with the lesser-known chatbots, and a higher portion of second-year students used ChatGPT. Third-year students also showed higher familiarity with more chatbots, showing a high reliance on AI technologies beyond the popular ChatGPT. Lastly, when comparing the fields of study, significant differences were not always shown among the fields, but when looking at individual degrees or subgroups in the field, differences were noted. The fields of study included: Technology (including Engineering), Social Sciences (including Law, Business, and Pedagogy), Humanities (including Theology and Art), Medicine and Healthcare, and Natural Science. Notable differences included: medicine and healthcare students were the least familiar with chatbots, while students in technology and engineering expressed the highest familiarity with ChatGPT; this group also used all chatbot applications to a significantly higher degree and had fewer concerns about the ethical aspects of AI usage in education.

Implications of this study discuss how these results can contribute to the design and implementation of educational technology and AI tools in the classroom (Stohr, Ou, & Malmstrom, 2024). If AIED tools like ChatGPT, other chatbots, or other AI simulations are integrated into courses, the identified differences in gender, academic level, and field of study should be acknowledged and addressed. The authors concluded that "Gender-sensitive approaches, tailored interventions, and inclusive design principles may be required to ensure that AI-powered educational solutions cater to the unique needs and preferences of various student demographics."

To gather perceptions of business communication instructors regarding use of AI in the classroom, a 2023 exploratory study by Cardon et al surveyed 343 business communication instructors from the United States, Canada, Europe, and Asia (Cardon, Fleischmann, Aritz, Logemann, & Heidewald, 2023). Analysis of the skills taught in the instructors' courses revealed 84% of these instructors were currently teaching business writing, 70% were teaching business presentations, 58% were teaching business reports, and 33% were teaching other writing topics. The survey consisted of both closed and open-ended questions. Key findings included 36.5% agreed that a change to their current teaching methods was inevitable, but 15.4% were resistant to incorporating AI into their courses. When asked how they could change their current teaching approach, 43.5% agreed that one effective use of generative AI would be for a first draft of a writing assignment to help students generate ideas for specific documents. The open-ended questions reinforced the overall analysis that change is inevitable with statements such as, *"We have adapted—going from an abacus to a calculator, an encyclopedia to Google. We will continue to accelerate through technology disruption."* Other statements supported the 46.7% of instructors who noted that they felt nervous or anxious about using AI-Assisted writing in their courses, for reasons such as, *"It is changing and developing faster than I can develop lessons about it."* The goal of business communication courses is to help students develop the skills they need to communicate effectively in the workplace. Instructors in the survey agreed that AI-assisted writing would be useful in the workplace (79.9%) and ultimately benefit the workplace by enabling professionals to accomplish tasks more quickly (84.5%) and increase productivity (72.6%).

McMurray (2024) reports that faculty members at the Carson College of Business at Washington State University have integrated ChatGTP in various business courses such as Economics, Management, and Marketing. For example, Lucas Smith is using ChatGPT to help students with economic modeling and real-life economic projects. Smith stated,*"Using ChatGPT really expanded my outlook on what the future workforce is going to look like and how our future employers will expect us to use AI models."* Professor Andrew Perkins also uses ChatGPT in his Marketing Management courses, where students use simulations to develop a brand, product, budget, communications strategies, and even 3-D models of their project.

The challenge will be finding a balance between teaching students the necessary AI tools needed in the workforce to be more productive while still requiring students to show individual ability and development in the required areas and skills covered in the course. As Fitria (2021) aptly states, "Education is not just about acquiring knowledge." The process of learning extends beyond the mere accumulation of information; it is a multifaceted experience that occurs both inside and outside the classroom. While students can acquire various concepts and skills and learn to apply them in professional and everyday contexts, AI plays a supportive role in facilitating this process. However, AI is limited in its capacity to teach essential human attributes such as empathy, sympathy, and other emotional and social skills, which are critical for functioning effectively within communities—whether in the workplace, classroom, or personal life. Despite AI's growing influence in education, it can never replace the vital role that teachers and educators play in shaping holistic learners.

This integration of AI enhances educational and professional environments by offering personalized and accessible learning tools. Artificial intelligence can support educational learning and serve as a valuable tool for businesses. Some examples identified by Fitria (2021) include the following:

1. Voice Assistants: These tools enable students and employees to easily search for materials, reference questions, articles, and books by simply speaking or mentioning keywords.
2. Presentation Translators: This technology is particularly beneficial for individuals with language or vision limitations, making it widely adopted for a variety of purposes.
3. Global Course Platforms: These platforms offer personalized features that notify students and employees about course progress, required study materials, test scores, relevant course recommendations, and more. AI-driven solutions enable schools, universities, and

businesses with international programs to create curriculum-based classes and provide tailored learning experiences.

Fitria (2021) concluded, “The existence of artificial intelligence may be able to provide knowledge to students, but developing character cannot be done. That is an educator’s job--how to inspire, motivate, and make students become good students. The role of the teacher in providing motivation, inspiration, and developing character is what AI cannot replace because AI is not given feelings and emotions like humans in general. In the end, if we look at technological developments, we must be able to adapt as technology advances. If we do not adjust, we are an educator (teacher/lecturer) that may be replaced by technology.”

As the recent studies discussed in the previous pages illustrate, challenges exist in higher education regarding effective usage of AI in the classroom and in student learning in general. Students are using various AI tools, but there are differences of opinion regarding their value and legitimacy. Some instructors embrace AI tools, while others question or even ban their use by students.

AI TOOLS USED BY STUDENTS

ChatGPT’s ease of use and free platform certainly helped launch AI onto the technology scene. However, while ChatGPT may have initially opened the door to introduce students, faculty, and businesses to the benefits of AI tools, multiple other AI tools are available and can project similar results. What AI tools would be most beneficial in the classroom or business environment? What AI tools should faculty introduce to students to broaden their AI knowledge and skills? What products are students already using?

As part of the search for AI tools used by students, the authors visited several websites to compile a list. Starting with Microsoft Copilot and Google Gemini, the search expanded to ChatGPT and other websites that were listed in the results during the original search. Using the prompt “Top AI tools used by college students,” the list below identifies the websites used in the search.

- https://kripeshadwani.com/best-ai-tools-for-students/#20-18-pdf-ai-
- https://copilot.microsoft.com/
- https://clickup.com/blog/ai-tools-for-students/
- https://gemini.google.com/app
- https://chatgpt.com/
- https://theprocesshacker.com/blog/ai-tools-for-college-students/
- https://www.computerscience.org/resources/ai-tools-to-help-you-study/
- https://www.aitoolmate.com/best-ai-tools-for-students/
- https://toolplate.ai/list/ai-tools-for-students
- https://back2college.com/study-tips/best-ai-tools-for-students/
- https://amberstudent.com/blog/post/best-ai-tools-for-students#strong1-open-ai-playgroundstrong

From the websites, a listing of 98 different tools was compiled. Table 1 displays the complete listing without any duplicates.

TABLE 1. 98 Unique AI Tools

Adobe Express & Firefly	AI Essay Writer	AIApply	Aistote
Anki	Ariana AI	AskCodi	Audiopen.ai
Braily	Brainly	Buddy AI	BypassGPT
Caktus AI	Canva	CareerDekho	Century
ChatGPT	ChatPDF	Clickup	Cognii
Conch AI	Curipod	Doctrina AI	Duolingo
Edmentum	Edubrain.ai	Eightify: AI YouTube Summarizer	ElevenLabs
ELI5	Elsa Speaks	Evernote	ExamCram
Fgeneds	Fireflies ai	Fobizz	Formula Bot
Fotor	Gamma AI	Geleza	Google Bard
Google Gemini	GPTionary	Gradescope	Grammarly
Haiku Deck	Hocoos	Huru AI	Jasper.ai
Jenni	Khan Academy	Kickresume	Kiwi Video
Knewton's Alta	Knowji	LanguagePro	Mathly
Mendeley	Microsoft Copilot Designer	Midjourney	Mindgrasp
MindMeister	Motion	Mubert	myEssai
Natural Readers	Notedly AI	Notion AI	OpenAI
Originality.ai	Otter.ai	PaperTyper	PDF AI
PDFGear	Perplexity AI	Quillbot	QuizGecko
Quizlet	Replika	Roshi AI	Scholarcy
Scite AI	Slidesgo	Smart Sparrow	Socratic by Google
Soofy	Speechify	Stepwise Math	StudyX
Summarizer	Summate	Todoist	Trellis
Tute.ai	TutorAI	Tutorly.ai	Undetectable AI
Unschooler.me	WolframAlpha		

Of the tools located, ten tools were listed across three or more listings. Table 2 displays the AI tools with multiple listings including the name, count of appearance, and website. The most popular AI tool across the lists was Grammarly, appearing on 9 of the 11 lists. Having the second most appearances, Otter.ai was found on seven lists. WolframAlpha appeared on six lists. ChapGPT and Notion AI both appeared on five lists, while Quillbot and TutorAI appeared on four lists. The remaining tools, Knowji, Quizlet, and Unschooler.me, appeared on three lists.

TABLE 2. Tools listed on 3 or more listings

Name	Count	Website
Grammarly	9	https://www.grammarly.com/
Otter.ai	7	https://otter.ai/
WolframAlpha	6	https://www.wolframalpha.com/
ChatGPT	5	https://chatgpt.com/
Notion AI	5	https://www.notion.so/product/ai
Quillbot	4	https://quillbot.com/
TutorAI	4	https://tutorai.me/
Knowji	3	https://www.knowji.com/
Quizlet	3	https://quizlet.com/login
Unschooler.me	3	https://unschooler.me/

Visiting each of the above websites for the frequently listed tools, a table was created using the AI tool name, the description of the tool verbatim from the website, the website url, and any pricing information posted. Table 3 displays these findings. The majority offer several versions, ranging from free, to a pro version for purchase, to enterprise level capabilities and higher prices.

As the various tables in this section of the paper illustrate, the number of AI tools that students may find useful in their course work is substantial. These tools are also pretty easy to find, as the authors found several that were listed on more than one website they searched for "top AI tools used by college students." Furthermore, most of the AI tools listed in table 3 have free versions available for students to use; and who doesn't like something "free," at least to try it.

CONCLUSIONS AND FUTURE RESEARCH

The introduction of ChatGPT and similar AI chatbots and tools has significantly transformed the landscape of higher education. Stakeholders, including businesses, educational institutions, and society at large, contend that AI is an essential instrument that must be integrated into the college curriculum to effectively prepare students for professional careers. While some research shows instructor hesitancy and concerns, others are finding ways to embrace AI in effective ways in their classrooms. Research studies show that students are using AI in their courses in numerous ways, and the current authors identified how easily the tools can be found by students.

Having compiled a comprehensive inventory of AI tools currently used by students, the authors intend to further investigate this area of AI. Future research endeavors will include surveying students at the authors' universities to determine their utilization of these prevalent AI tools and the specific contexts in which they utilize them. Additionally, students will be asked to identify other frequently used tools that are not included in the initial list, as well as to share their perceptions regarding the role of AI in their coursework and future careers. Subsequently, the authors plan to survey faculty at the same institutions to gain insights into their current and anticipated use of AI, their perceptions of AI as a pedagogical and professional resource, the policies governing AI usage in their classrooms and institutions, the training related to AI provided by the universities, and their concerns regarding AI technologies.

TABLE 3. Frequently listed AI Tools

Name	Description from Website	Pricing
Grammarly	"an AI writing partner that helps you find the words you need—to write that tricky email, to get your point across, to keep your work moving." https://www.grammarly.com/	Free/pro/ enterprise
Otter.ai	"The #1 AI Meeting Assistant. Never take meeting notes again. Get transcripts, automated summaries, action items, and chat with Otter to get answers from your meetings." https://otter.ai/	Free/Pro/ Business/ Enterprise
WolframAlpha	"Compute expert-level answers using Wolfram's breakthrough algorithms, knowledgebase and AI technology." Areas include mathematics, science & technology, society & culture, everyday life. https://www.wolframalpha.com/	Free/Pro/ Pro Premium
ChatGPT	"Just ask and ChatGPT can help with writing, learning, brainstorming, and more." https://openai.com/chatgpt/	Free/ Subscription/ Enterprise
Notion AI	"One tool that does it all. Search, generate, analyze, and chat" SEARCH: find answers from Notion, Slack, Google Drive & more; GENERATE: create & edit docs in your style; ANALYZE: get insights from PDFs & images; CHAT: access knowledge from GPT-4 & Claude. https://www.notion.so/product/ai	Free/ Plus/ Business/ Enterprise
Quillbot	"We use AI to strengthen writing and boost productivity—without sacrificing authenticity." Eight tools in one platform: Paraphraser, grammar checker, plagiarism checker, AI detector, summarizer, citation generator, translator, flow. https://quillbot.com/	Free/Premium
TutorAI	"Create a custom learning pathway to help you achieve more in school, work, and life." https://tutorai.me/	Subscription
Knowji	"Knowji is a new approach to learning vocabulary. Knowji's vocabulary apps combine scientifically proven methodologies with entertaining content to create a thoroughly engaging and effective learning platform." https://www.knowji.com/	Could find no pricing info nor app in the Apple store
Quizlet	"Create your own flashcards or find sets made by teachers, students, and experts. Study them anytime, anywhere with our free app." https://quizlet.com/	Free; has app
Unschooler.me	"Teach and Learn with AI: generate courses with educational videos for any question." https;//unschooler.me/	Free/Pro/ University

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THE APPLICATIONS AND VIABILITY OF ARIMA MODELING USING CURRENT EMPLOYMENT STATISTICS

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ABSTRACT

The Bureau of Labor Statistics (BLS) sends out the Current Employment Statistics (CES) survey to compile employment data, which it aggregates and publishes monthly (Bureau of Labor Statistics, 2023). Individual states can apply additional methodologies for data collection; for example, California provides geographical levels, including county, region, and metropolitan areas (Employee Development Department, State of California, 2023). The CES data forms a time series of total employment, hours worked, and payroll earnings that can be analyzed using data mining techniques to create forecast models.

There is research showing that Autoregressive Integrated Moving Average (ARIMA) models and seasonal ARIMA (SARIMA) can be used to forecast other economic data like GDP, future jobs, stock prices, salaries, and wages (Abonazel & Abd-Elftah, 2019; Ajmera & Clinton, 2016; Alyahaya & Hadwan, 2022; Mondal, Shit, & Goswami, 2014; Toledo, 2022), and other models have been used for CES data (Dixon & Tucker, 2016). However, research appears lacking in applying ARIMA directly to CES data. Therefore, this study aims to investigate the potential development of ARIMA models and their use in analyzing and predicting employment trends in the CES survey data.

The three research questions to guide the development are “What are the overarching trends within state CES data,” “How do data mining methodologies create valid models for measuring and predicting future CES data values,” and “What variant of ARIMA analysis is optimal for CES analysis?” To address these questions, we present the creation of an ARIMA model using the Akaike Information Criterion and the Bayesian Information Criterion to analyze total employment from CES data. The data will focus on California’s total employment from Extended Abstract for Presentation 1939 to 2023 (Employee Development Department, 2023), and we will demonstrate the model’s validity and accuracy through coefficient analysis, residual analysis, and the Ljung-Box Test. Comparing metrics of various ARIMA models shows that a seasonal ARIMA model accurately models the underlying total employment data and optimally forecasts future employment.

Keywords: *ARIMA modeling, Statistics, Data Mining, Employment Analysis, Current Employment Statistics, Residual Analysis*

CHAPTER 1: THE FOUNDATION OF THE STUDY

Every month, the Bureau of Labor Statistics (BLS) sends out a survey to businesses for the purpose of collecting data on various employment metrics. In this survey, the prioritized metrics of employment are the number of filled jobs within a specific sector of the workforce, average hourly earnings, average weekly hours, and total real earnings. At the end of the month, BLS collects, aggregates, anonymizes, and publishes the data that the Current Employment Statistics (CES) survey collects. The CES data itself is published as an independent data series for each metric that BLS collects in the CES survey.

In addition to the federal efforts by BLS, individual states can create additional methodologies for CES documentation and publication. California for one makes an independent publication of CES data with a geographic level of distinction published directly in the dataset. California publishes data at various levels of geographic distinction including county, region, and metropolitan area. The California Employment Development Department (CEED) publishes an additional set of CES data. Although the CEED is a separate governmental entity, they use methods compliant with the guidelines and requirements established by BLS.

To this day, the data produced by the CES survey remains one of the most consistent and reliable sources of employment data for the United States. Further, the trends that appear when analyzing this data can serve as general economic indicators. Various researchers and economists have analyzed trends present within CES data, but as tools and methods for data analysis have progressed, the lack of implementation and application in CES research has created a vacancy in the field. Application of data mining in CES analysis can lead to new revelations and techniques within the realm of CES research.

Background of the Problem

A crucial skill for business owners is understanding the employment trends within their community. Being able to analyze and understand trends within their business environment assists with creating and maintaining business practices to ensure competitiveness in the business environment (Bartik, 1985). Analysis of employment trends can also highlight indicators within the market such as average pay, hours worked, and numbers of jobs within the industry. In addition, understanding industry trends and indicators can serve to reduce risk within business decision making (Plaziak & Szymańska, 2014).

Furthermore, one of the largest decisions a business can face is choosing a location for operations (Bartik, 1985). Choice of location is impacted by the trends of employment and job opportunities present within the target community. A region with an elevated level of employment for an industry can provide confidence that the region in question has resources and attributes ideal for the industry. Conversely, a region with low employment for an industry can represent a niche in the market and a lack of competition. Many of the differences between regions seem insignificant, but each difference compounds into creating business climates within a region that are significantly different from one another (Plaziak & Szymańska, 2014). While analyzing employment numbers exclusively does not provide enough information alone for such a decision, an analysis of employment numbers can be used to assess the market and improve decision making.

To this end, CES data has been analyzed and cited in a broad sense, with most studies revolving around a specific industry or metric. These studies are focused on creating a snapshot of the current industry and using this snapshot to compare the current state of an industry to the state of the industry some time ago. However, as data mining methodologies have been created to further advance the data analytics industry, research analyzing CES data has not adopted the widespread use of data mining methodologies. As a result, data mining methods on CES data are not documented.

Problem Statement

Data mining techniques have yet to be widely applied in CES analytics, and the documentation detailing methodologies and results from CES data mining are nonexistent. Thus, the problem addressed by this study is twofold. Firstly, no documentation exists for creating data mining models for CES analysis. Secondly, no analysis has occurred to determine the validity or invalidity of data mining applications for CES data.

Purpose of the Study

The purpose of this study is to apply data mining techniques for the CES analysis, assess the validity of data mining models created through use of CES data, and thoroughly document the creation process so that other can readily and reliably recreate the process, This purpose addresses the problems stated above by creating, validating, and documenting the process of creating a data mining model using CES data as a new application in the realm of CES analysis.

Research Questions

This project will attempt to answer the following questions.

- What are the overarching trends within state CES data?
- How do data mining methodologies, such as ARIMA, create valid models for measuring and predicting future CES data values?
- What variant of ARIMA analysis is optimal for CES analysis?

Significance of the Study

Various forms of CES analysis have been completed in the past. However, these studies (Lim et al, 2023; Kässi & Lehdonvirta, 2018; Desmet & Fafchamps ,2005) have been limited in their methodology and scope. Analysis has been done to analyze trends within a specific industry, typically within ten years. In addition, CES analyses have been done to analyze trends within a certain demographic, such as analyzing the proportion of women within an industry or the workforce at large (Mance, 2021; Lui et al, 2023; Forsythe et al, 2020). These forms of analyses use data visualization tools to analyze the trends apparent in this data over time.

There are also numerous economists who study employment statistics. Many economists make models and predictions for future trends in the economic ecosystem (Lepoutre, 2022; Sargent Jr, 2017). These predictions range in scope from specific industry-level trends to predictions regarding emerging technologies within the workplace. However, only predictions based on the total number of jobs and employment opportunities available cite CES data relevantly.

However, studies scarcely apply data mining methodologies to CES data, and many economist's models are not built with an emphasis on data mining techniques. This study will focus centrally on the applications of data mining techniques for CES analysis; the techniques applied will identify trends within the long-term data and identify similar trends across different geographic regions. To conclude, a predictive model will be established to determine if high-precision predictive models can be created for CES analysis.

Definition of Terms

Bureau of Labor Statistics (BLS): The Bureau of Labor Statistics is a government organization responsible for surveying and recording facts and statistics regarding economic performance and the labor economy (Bureau of Labor Statistics, 2023). One of the main methods BLS uses is sending out surveys to companies and consumers to gauge various measures of economic activity (Bureau of Labor Statistics, 2023). Notably, one of these surveys is the Current Employment Statistics (CES) Survey which measures various employment statistics such as number of jobs, average pay rate, and average hours per work week. BLS publishes its various data sets publicly on its website for agency and independent research.

Current Employment Statistics (CES): The Current Employment Statistics (CES) survey is a survey sent out monthly by the BLS (Bureau of Labor Statistics) that gathers employment measures including the number of jobs available, average pay rate, and average working hours per week (Bureau of Labor Statistics, 2023). These statistics are broken down and aggregated by industry and region. The data for each industry, as well as the data for each state and major metropolitan area, are published as an independent data series accessible separately from the national CES data series (Bureau of Labor Statistics, 2023). In addition to the federally published data series, individual states can publish their CES data separately and aggregated by different regions and values than the national CES data set (Employment Development Department, 2023). However, for a state to publish CES data, the state's methodology must be compliant with the guidelines and standards established by the BLS's CES methodology handbook. This stipulation ensures that the state-published data is equally as credible as the national data. The details of the data collection process for CES data are outlined in chapters 2 and 3.

Unemployment Insurance (UI): Unemployment Insurance is filed when companies lose employees. The records of unemployment insurance are reported by employers quarterly (bureau of Labor Statistics, 2023). Unemployment Insurance records are referenced in the collection efforts of CES surveying as companies with substantial changes in their UI report are more likely to be selected for sampling in the collection of CES data (Bureau of Labor Statistics, 2023). In the publication and preparation of CES data, UI references are utilized in the sampling and benchmarking process. While UI claims and reports are not extremely impactful in the overall measures of CES data, they fulfill an important purpose in validating CES results prior to publication. The exact impact of UI on CES results is elaborated further in chapter 2.

Data Mining: Data Mining is an umbrella term for various data analysis methods of large data sets. The core purposes of data mining are to identify underlying patterns within the data, theorize and document the relationships between variables, and create models that attempt to explain the largest amount of variance within the data set (Mondal et al, 2014). There are numerous data mining methodologies, all of which with unique individual advantages and disadvantages, but all data mining methodologies all serve to fulfill the same underlying purposes.

ARIMA Modeling: ARIMA modeling is a data mining technique designed to track movement of a dataset's mean over time (Mondal et al, 2014). This core self-regression exists at the heart of all ARIMA methodologies. However, variants of ARIMA methodology exist based on the auto-regressive, integrated, and moving average properties of ARIMA models (Mondal et al, 2014). These models are differentiated with the format ARIMA(p, q, d), where p represents the auto-regressive order of the model, q represents the differencing iterations to achieve stationarity with the model, and d represents the moving-average order of the model (Mondal et al, 2014). A branch of ARIMA variations designed to model seasonal variations within data exist (Dimri et al, 2020). These seasonal ARIMA (SARIMA) models contain a separate set of ARIMA parameters to forecast the seasonal variation. The notation for SARIMA models follows the pattern of SARIMA(p, q, d), $(P, Q, D)_m$, where P, Q, and D represent the ARIMA parameters for seasonal variation, and m represents the seasonal difference of the seasonal time series trend (Dimri, et al, 2020). Within the variations of ARIMA and SARIMA models, various goodness-of-fit measures compare each model to determine the most accurate and viable model Overall, ARIMA is a highly versatile data mining method that can be tailored to the needs of induvial analyses and datasets.

Predictive Modeling: Predictive modeling is another data mining method that focuses on predicting an unknown case (Verhagen, 2018). In time series data, this unknown case is the future state of the data (Verhagen, 2018). However, by analyzing the trends in the present data over time, we can create a model that predicts future changes in the data.

Assumptions, Limitations, and Delimitations

Assumptions

The first underlying assumption of this project is the accuracy and validity of CES data as an accurate indicator of economic condition and performance. All further processes will be based on the data produced by the CES survey, and the assumption of accuracy is necessary to base conclusions on CES data. Independent studies have been conducted to determine the level of accuracy of CES data, and they have demonstrated that CES data can be a reliable economic indicator (Ajmera & Clinton, 2016). These studies and their results are discussed further in detail in Chapter 2.

Limitations

One of the base limitations of all research utilizing CES data is that CES data does not encompass all forms of employment. Within the establishments governed by UI taxes, private households and agricultural businesses are not included within the CES survey. In addition, there are various forms of work that are not included within the scope of CES data. These forms of work include students getting paid through a work study program, independent and contract insurance agents, employees of non-profit and religious organizations, and railroad employees whose UI is covered by the Railroad Retirement Board. Furthermore, proprietors and self-employed persons are excluded. As such, these populations are unable to be analyzed using CES data.

Another base limitation is that CES data that is broken down into various geographic regions is only available for the years 1990-2023, and as a result, implementing data from before 1990 will result in lots of noise within the models.

Delimitations

The central delimitation present within this study is that this study only concerns CES data from the state of California. This choice is due to the availability of CES data that is aggregated at the county, metropolitan area, and state level that is published by the state of California separately from the federal CES publications.

Summary

Overall, there is much potential in the application of modern data analysis techniques for CES data. The niche that is present within the field of CES analytics allows for a level of innovation in the techniques applied to CES data. Furthermore, the role the CES data serves as an accurate economic indicator, which can serve as genuine inquiry to the current state of various industries and the economy, which raises the CES data's value as a target of analysis; the understanding of industry trends and the analysis for CES data can provide value to individual businesses.

Moving forward, the analysis of the CES data is the central goal. However, properly applying data analysis techniques requires a deep understanding of various aspects of CES data. Understanding the method and processes used to generate CES data, analyzing the methods that have been applied to analyze CES data, and understanding the different implications of CES analysis results are all crucial to understand before we start our own analysis.

CHAPTER 2: A REVIEW OF THE PROFESSIONAL AND ACADEMIC LITERATURE

From a business perspective, understanding the overarching business environment of your region is critical to success. Understanding the current employment trends within a region can positively impact the results of business decisions regarding workforce planning, economic foresight, consumer behavior, and workforce competition (Bartik, 1985).

Understanding the impact and importance of trends and statistics within employment is imperative, as business professionals can use their knowledge of these trends and statistics to create a positive business impact (Plaziak & Szymańska, 2014). The central purpose of this review will be to determine the extent to which employment statistics have been analyzed and applied within business as an industry.

In my literature review, two primary objectives exist. The first objective is to discuss the data set this project aims to analyze. As such, the first portion of the review will be dedicated to detailing the Bureau of Labor Statistics (BLS) and their Current Employment Statistics (CES) survey. The most important features of the CES survey to understand are the survey structure, the data collection methodology, and the applications and implications of the CES estimation process. Afterward, a compilation of different research projects highlighting the current state of CES analysis will occur. Much of the research using CES data falls into one of three categories: demographic or sector analysis, spatial distribution analysis, and CES response analysis. Sector analysis focuses on identifying trends for one sector or demographic. Spatial distribution analysis identifies geographic trends in employment. CES response analysis focuses on identifying trends in employment in response to world events (Frothingham & Brunsdon, 1999). All three categories of research are sampled below.

BLS and CES Methodology

However, before addressing the topic of employment data analysis, we must understand the formatting, processes, and limitations of the publicly available employment data. The core measures of the CES survey are total employment (defined as the number of workers in a specific job), average working hours per week, and average pay rates within the United States Workforce (Bureau of Labor Statistics, 2023). BLS directly surveys businesses, although survey participation is only mandatory for the regions of New Mexico, Oregon, South Carolina, and Puerto Rico (Bureau of Labor Statistics, 2023). In addition to the BLS survey sent directly to businesses, BLS also queries the records of governmental agencies to gather employment data from public sector employment (Bureau of Labor Statistics, 2023). This secondary data gathering provides redundancy that partially accounts for nonrespondents of the initial CES survey. Accessing their data source reveals that the data includes fields for the time of data collection (month and year), and the associated number for the input sector (either total jobs, work hours, or pay).

California sends out an additional survey to businesses to gather CES data. While the California survey is not directly related to the federal CES, the methods used to gather Californian data are compliant with the guidelines defined by the CES Methods Handbook (Employee Development Department, 2023). The data catalogued by California does not include data regarding work hours or pay. Instead, the Californian CES data splits the data into various geographic partitions. In addition to statewide metrics, California publishes data for individual counties and metropolitan areas. While the lack of various fields indicates the Californian CES data is less thorough than the federal CES data, the addition of geographical data allows possibilities of geographical analysis of the data.

The numerical estimates that appear in the final CES records are based on a probability sampling model. The probability sampling model predicts the ratio of growth from one month to another by calculating weighted trends present in companies that have reported previously (Robertson, 2017). When companies who have reported on previous surveys send in their employment data for the upcoming survey, the new data is used for the summation of employment data rather than the estimate (Robertson, 2017). In situations where companies have reported in prior surveys, but have since ceased reporting, estimates are utilized. However, if companies do not send in their employment data for the CES survey, the estimates used to replace the data are not reused in the calculation for next month's weighted estimate (Copeland, 2003). The estimates used in this process derive from the estimates produced in the Quarterly Census of Employment and Wages published by BLS. In addition, the state gathers the CES data using a unique estimation technique based on an employment value based on the state census, which is simpler, but requires the states to revise more entries than the national CES data (Robertson, 2017). Another nonresponse benchmarking method implemented by BLS is by using previous data to estimate the current month's data. Initially, this process can introduce a large amount of variance and bias within the data, but as the preceding data gets larger, the variability and bias introduced in this process lowers significantly (Dixon & Tucker, 2016).

Like other data sets, CES data is subject to fluctuations in the numbers. One of the most common fluctuations in employment statistics is seasonal fluctuations in jobs during the summer and winter months (Mullins, 2016). To increase data transparency under the effects of seasonal fluctuation, BLS also publishes both adjusted and unadjusted data for seasonal fluctuation (Mullins, 2016). This inherent property of CES data results in a minor negative effect on CES model performance; this property further allows testing for unique seasonal trends within each industry and sector of the CES data (Phillips & Wang, 2015). Despite these fluctuations and seasonal trends, CES data maintains integrity by keeping work sectors independent from one another. The mathematical method used by BLS has changed over time to discern seasonal trends more accurately from random variations in employment level over time (Phillips & Wang, 2016).

Another source of fluctuation is when businesses start or end. Initially, the job gains from new businesses are approximated to be equal to the job loss from business death, but this assumption is not precise. To improve the performance in this case, the BLS uses an "autoregressive integrated moving average" (ARIMA) methodology to account for any residual effects present within the data (Mullins, 2016). The extensive research and design that backs the development of BLS methodology validates CES data as an accurate indicator of monthly employment change within various industries (Bowler, 2006). Other than problematic fluctuations that occur within the labor market, there are also assumptions and possible biases in the design of the CES survey that need exploration.

Firstly, the CES survey methods define employment as “the total number of persons on establishment payrolls employed full- or part-time who received pay (whether they worked or not) for any part of the pay period that includes the 12th day of the month.” (Bureau of Labor Statistics, 2023). The implication underlying this definition is that the recording of employment data through CES methodology is reliant on the querying of Unemployment Insurance (UI) data (Bureau of Labor Statistics, 2023). This definition conflicts with other definitions of employment as CES data does not report data for self-employed workers, school workers paid via work-study programs, employees of state and local governments, independent insurance agents, and workers of non-profit organizations (Bureau of Labor Statistics, 2023). Workers in the agricultural sector of the economy are also excluded from CES reporting, as there are many exceptions available to agricultural workers to not be included in UI administrative records (Bureau of Labor Statistics, 2023). In addition, CES data would also not record data for employees who spent extended periods of time unpaid (due to illness, injury, leave, etc.) (Hussmanns, 2007). This exclusion may result in underreporting employment numbers and necessitates testing the CES data for statistical significance by analyzing sample errors of the last twelve months of CES data at the 90 percent significance level (Hussmanns, 2007).

In addition to the CES survey, BLS publishes an alternative measure for employment titled the Current Population Survey (CPS) that measures employment. However, the methodology of the two surveys differs. The CES survey measures employment by surveying businesses; the CPS survey measures employment by surveying households (Bower, 2006). While CPS is also a significant and accurate measure, it is largely focused on collecting demographic data, rather than data that reflects the overall economic climate (Bower, 2006). In addition, the CPS was temporarily ceased in 2005 and reinstated in 2017, so there is a twelve-year irreconcilable gap in the data (Kassi & Lehdonvirta, 2018).

Despite fluctuations within CES data and estimations, CES data remains a reliable source for businesses to use for employment and market analysis. CES data has a long-running history that is consistent and provides one of the few sources of large-scope industry-classified data (Ajmera & Clinton, 2016). These industry-level indicators are commonly used by businesses to understand the state of their industry in their area, and can inform decision-making relevant to hiring, firing, and plans for an organization (Ajmera & Clinton, 2016). Furthermore, applications of CES data include use as an economy-wide indicator used by organizations such as the Bureau of Economic Analysis (Ajmera & Clinton, 2016).

However, most users of CES data are interested in short-term and long-term forecasting of economic conditions, either for business or personal use (Chi & Leslie, 2015). The availability and scope of the data, and the number of users the BLS has aggregated over time with this data, led to a series of analyses done within recent history.

An entire range of analyses designed to analyze changes in CES data during the 2020 COVID-19 pandemic exists. During the pandemic, employment numbers were significantly lower than in previous years due to widespread illness and government-ordered quarantines (Dalton et al, 2020). Fortunately, employment data during this time was relatively easy to track by analyzing vacancy postings, unemployment insurance claims, and business bankruptcy claims (Dalron et al, 2020). As such, the analyses of changes during the 2020-2021 CES data prioritize finding discrepancies within the employment changes based on demographic data.

One of the major vectors of variance among COVID-era CES data is the state response to the pandemic. According to the analysis of labor market loss, the level and intensity of the state's response to the pandemic did not cause a significant change in the percent change in the overall market change (Forsythe et al, 2020). However, one significant factor in the percent change in the labor market was the timing of the State response measures. The states that implemented pandemic responses earlier experienced a greater negative effect on the labor market compared to states that implemented pandemic response measures later (Forsythe et al, 2020). In addition, the lifting of pandemic response measures did not result in an immediate resurgence of employment, which is theorized to result from consumers and business owners having an overall lower sense of confidence in the economy during the COVID-era economy. (Forsythe et al, 2020).

Exhibiting a similar pattern, differences between the effects on different work sectors exist. Due to quarantine exceptions for "essential workers", there was a significant difference between the employment data for essential and non-essential industries (Forsythe et al, 2020). Sectors such as hospitality and fashion experienced drastic loss in employment, while essential retail sectors such as produce, groceries, and delivery companies experienced large increases in employment, while sectors such as nursing and healthcare had much less drastic changes in both positive and negative directions (Forsythe et al, 2020). This discrepancy is directly related to the nature of the federal response to the pandemic affecting different industries disproportionately.

A partial explanation for COVID-era trends in employment can be observed by analyzing CES data along the metric of company size. When the CES survey results are analyzed along the parameter of respondent size, it shows that companies with less than ten employees were the least likely to fire employees, but the most likely to die (Dalton et al, 2020). The impacts on companies between ten and five hundred employees are less likely to experience company death, but still suffer significant employee loss (Dalton et al, 2020). Companies with greater than 500 employees experienced the lowest amount of employee loss but also had the slowest rate of employee return (Dalton et al, 2020).

Going forward, this project will not study the implications of the COVID-19 pandemic on the current labor market, but analyses of the impact of the pandemic makes up a sizable proportion of the published CES research in the last 5 years.

In a broader sense, research has been done to analyze CES data and methodology shifts in response to natural disasters. The immediate effect of a natural disaster on employment is a sharp, sudden decrease in employment. The drastic nature of employment changes following natural disasters provides a challenge to CES officials, as not all the assumptions of CES hold true when applied to a disaster area (Mance, 2021). In particular, the CES estimates for the birth and death rates of businesses are consistently inaccurate for disaster areas (Mance, 2021). The CES estimates for nonrespondents are inaccurate when based on previous CES data; however, when new direct estimates are taken based on the respondent data, the resulting estimate is unbiased, and can be taken to be fairly accurate, but is subject to a very high level of variance, particularly when the sample size is small (Mance, 2021).

Analyzing trends in CES survey responses in the past three years shows several trends to acknowledge. Firstly, since November 2020, the monthly change in employment in non-farm sectors has been positive, with a single exception in December 2020 (Gould, 2023). However, employment numbers have still not reached the level that was projected pre-pandemic (Gould, 2023). Other metrics, such as percent change in hourly earnings and percentage wage growth have either reached or exceeded pre-pandemic levels (Gould, 2023). These details are also expressed doubly in the BLS yearly publication (Bureau of Labor Statistics, 2023).

Benefits of Understanding Economic Indicators

Among other uses, CES data serves both as an economic indicator and an input into other economic indicators (Ajmera & Clinton, 2016). Many forms of economic analysis rely on economic indicators as analysis targets and as such a significant portion of economic analysis relies, either directly or indirectly, on the data provided by the CES survey (Ajmera & Clinton, 2016). The analysis of economic indicators allows businesses and economists to identify and respond to trends within the national and local economy provides information that positively influences the business decision process.

Nationally, economic indicators provide a measure of overall economic development within a country and inform government officials about dictating governmental policies regarding economic regulation (Bajraktari et al., 2022). Various indicators, such as employment level and employment demographics, highlight trends within the workforce, as well as trends within specific subsets of the workforce. This information can be presented to lawmakers, which can influence policy development and allow countries to identify weaknesses within the national workforce and change policy to compensate for this weakness (Bajraktari et al., 2022). Furthermore, the information provided by economic indicators leads to positive economic changes given that lawmakers address the concerns raised by economic indicator data (Deda et al., 2020). On a smaller scale, businesses can experience similar levels of positive influence on policy development through economic indicator analysis.

Small and Medium Enterprises (SMEs) face unique struggles within the economy. Due to the lack of resources that large enterprises have access to, SMEs are more vulnerable to changes in economic climate (Dvorsky, 2021). Addressing this vulnerability requires proper risk management implementation. Furthermore, macroeconomic indicators strongly indicate the level of risk for SMEs across the entire economy (Dvorsky, 2011). However, analysis of economic indicators can equip SMEs with the ability to draw conclusions regarding the greater economic environment, which can influence business practice and decrease risk, which can lead to an overall positive business impact (Dvorsky, 2011).

The impact of economic indicators on organizational performance highlights the importance of economic indicator analysis. A study by Markic et al. in 2022 demonstrates the existence of a significant difference in the organizational performance between organizations that utilize economic indicator analysis and organizations that do not. Over time, this difference in performance can lead to long-term significant increases in performance metrics (Markic et al., 2022). These differences in performance result from the incorporation of knowledge discerned from economic indicators into business technology, policy, and methodologies (Markic et al., 2022).

CES Analysis Research

Other researchers have focused on one specific region or demographic within the CES survey results. In research published by the Center for Construction Research and Training, the distribution of women in construction and other blue-collar sectors yields interesting trends. Firstly, the distribution of workers within the construction industry is heavily skewed towards men, who make up approximately ninety percent of construction sector employment (Liu et al, 2023). This level is significant for having a lower concentration of women than most industries, and notably are highly concentrated in administration and support positions within construction companies (Liu et al, 2023). Despite this steep distribution, the number of women in construction, both as admin positions and blue-collar positions, has been increasing steadily since 2011 (Liu et al, 2023).

The Congressional Research Service published an analysis report for trends in Science and Engineering jobs. The trends indicate that the Science and Engineering industries have improved by various metrics since 2016, and BLS estimates show that this growth is likely to continue (Sargent, 2017). In addition, the science and engineering industries have other positive economic indicators including high job growth rates, low unemployment rates, and high levels of projected growth over the next ten years (Sargent, 2017). These indicators of science and engineering jobs can inform policymakers, as well as science and engineering professionals, about the state of the industry and future trends.

The BLS published a report producing diffusion indices for employment data from 1991 to 2021. In the diffusion matrix, each measure is given a value of 0 to 100, where 0 represents every economic indicator moving in the negative direction, and 100 represents every economic indicator moving in the positive direction. The diffusion indices for state-level regional divisions are more variable than the diffusion indices for metropolitan areas (Lepoutre, 2022). With the exception of the recession starting in February 2020, the average value for the diffusion indices varied slightly around the average value of fifty (Lepoutre, 2022). In addition, the value of each index also follows the business cycle of regression and expression (Lepoutre, 2022). Lastly, in April 2020, every state within the state-level regional division index had a value of 0 (Lepoutre, 2022). Looking forward, these diffusion indices can be used as comparative economic indicators, but they can also be used for measuring the geographic distribution of jobs within the United States.

Another branch of CES analysis focuses on identifying spatial distributions of specific jobs or sectors. A spatial analysis of “green jobs” (jobs that center around energy alternatives to fossil fuels) reveals an underlying issue that green energy companies face. Firstly, the skills required for fossil fuel industry jobs are like job skills required for green jobs (Lim et al, 2023). In addition, the demand for green energy has led to a steadily increasing number of green jobs. The demand for skilled workers in green jobs has led green companies to attempt to hire former fossil fuel industry workers. However, the geographical concentrations of fossil fuel and green jobs are substantially different (Lim et al, 2023). This makes it difficult for fossil fuel workers to apply for green jobs without relocating, which results in green energy companies struggling to recruit former fossil fuel workers.

A county-level spatial analysis of various work sectors has been performed on the data from 1970 to 2000. There have been two studies here to contrast. One study by Desnet and Fachamps in 2004 uses a benchmark model with sector and aggregate capabilities. The other study by the same researchers conducted in 2006 used a deterministic convergence model to analyze county-level data.

The 2004 model shares several interesting trends. The benchmark model shows that every sector has been exiting sector-specific clusters (Desnet & Fachamps, 2005). However, within urban metroplex areas, service sectors are becoming increasingly concentrated in high-employment areas (Desnet & Fachamps, 2005). This poses an interesting dynamic, where non-service sectors are becoming increasingly distributed across the United States, but metropolitan areas are monopolizing and thriving due to a high concentration of service sectors. Furthermore, the model indicates that counties with higher levels of employment experience economic growth at a faster rate, which leads to accelerated growth in urbanized areas (Desnet & Fachamps, 2005). This also means that service sector employment will naturally grow incredibly quickly in clusters.

In the 2006 publication, the convergence model reflects and adds nuance to many of the conclusions of the 2004 publication. In the convergence model, the difference between service and non-service sectors is even more prominent. Service sectors have been heavily concentrated in aggregate clusters (Desmet & Fafchamps, 2006). This finding can be interpreted alongside side other models that deconcentrate in metropolitan areas to evidence that while larger counties with metropolitan areas are deconcentrating, smaller counties with lower employment are concentrating (Desmet & Fafchamps, 2006). In addition, not all sectors abide by this pattern. This is true for service sectors, but manufacturing sectors are deconcentrating (Desmet & Fafchamps, 2006). The varying patterns of concentrating and deconcentrating sectors have many implications, but a formal statement of the implications on productivity, wages, and employee and employer satisfaction is not included in this model.

Arima Analysis

ARIMA analysis has proven to be an effective methodology to study variations in various time series data. Understanding the applications of ARIMA methodologies in other studies reveals the potential benefits of ARIMA methodology application to CES data.

In a 2014 study, Mondal, Shit, and Goswami applied ARIMA methodology to create a predictive model that forecasts future stock prices. In their study, the application of ARIMA modeling to stock prices created a highly accurate model for stock price prediction using the data generated by the National Stock Exchange (Mondal et al, 2014). However, in this instance, the ARIMA created did not facilitate a significantly higher level of accuracy than other stock prediction models. However, despite the lack of improvement over other competing models, the model generated by the researchers maintains a high level of accuracy and precision in its predictions.

Another economic model proposed by Abonazel & Abd-Elftah in 2019 uses ARIMA methodology to predict future Egyptian GDP values. Their model accurately predicted the Egyptian GDP for 10 years after the original source data had ended. Furthermore, the researchers used various goodness-of-fit measures including Mean Square Error, Akaike Information Criterion, and the Bayesian Information Criterion (Abonazel & Abd-Elftah, 2019).

Use cases for ARIMA analysis exist within non-financial sectors of the workforce as well. In the agricultural sector, ARIMA applications provide crucial information about various meteorological measures such as temperature and rainfall (Murat et al, 2018). In this study, researchers compared data from distinct geographic sectors to identify differences between the different regions through their statistical trends (Murat et al, 2018). Furthermore, the researchers derived multiple predictive models for each region, which increased the dimension and depth of the analysis (Murat et al, 2018).

A study by Petrevska in 2017 demonstrates the applications of ARIMA analysis in the tourism industry. While an ARIMA model maintains a high accuracy in modeling tourism, as Petrevska's model was more thoroughly analyzed, various stability concerns arose. Upon further analysis, multiple structural breakpoints exist within the underlying data (Petrevska, 2017). These breakpoints partially undermine a potentially valid and satisfactory model. Despite goodness-of-fit measures ensuring the validity of the ARIMA model for tourism, these structural breakpoints suggest that other forms of analysis can represent the underlying data more accurately (Petrevska, 2017). This study largely presents some of the limitations of ARIMA modeling, and presents situations and data sets that may not be viable for ARIMA analysis.

An ARIMA analysis of traffic patterns by Alghamdi et al in 2019 highlights various strengths of ARIMA methodology. Other models struggled to properly analyze levels of traffic congestion due to the non-normality of traffic time series data (Alghamdi et al, 2019). Furthermore, the researchers demonstrate that analysis of residual points within an ARIMA model reveals further information about white noise within the model, which can lead to improvements in model performance (Alghamdi et al, 2019)

More central to the themes of this project, ARIMA modeling has found use by various researchers studying data related to employment. In 2022, Toledo authored a study in which he created an ARIMA model to forecast employee wages for a Filipino mining company. This ARIMA model proved to be stable after the initial modeling period (Toledo, 2022). While Toledo's study operates on data of a smaller scale (both temporally and geographically) than Californian CES data, Toledo's study remains significant as an explicit example of ARIMA analysis applied to job statistics data.

In addition to employee wages, researchers have estimated total job statistics for other countries. In 2022, researchers Alyahya and Hadwan created an ARIMA model to estimate the total number of jobs within the IT sector of the Saudi Arabian workforce. The delimitation of studying specifically IT sector positions limits the overall implications of the model, but despite the limited scope, the researchers ARIMA model performs well (Alyahya & Hadwan, 2022).

Alyahya and Hadwan's model demonstrates that ARIMA methodologies can be effectively utilized for the forecasting of employment data.

Summary Conclusion

The CES survey process has evolved from the original methodology, and the current state of CES methodology and data has cemented the CES statistics as an accurate and reliable economic indicator. To this end, analyses measuring the reliability of CES data and its impact on a national and business scale exist. The accuracy of CES data enables the analysis of CES data for specific industries and regions to discern localized trends and provide economists information to predict future trends.

Furthermore, ARIMA methodologies have repeatedly proven their potential to create highly accurate predictive models using various source data. In particular, the fact that effective ARIMA models based on economic and employment data highlight the potential benefit of ARIMA methodologies for CES analysis.

CHAPTER 3: METHODOLOGIES

In this chapter, discussion of the methodologies utilized in this research exists. The discussion found within this chapter will cover the research design, research questions, research setting and participants, as well as methodologies on data collection, data analysis, and validity testing.

Research Design

The base of this project's design is an archival research approach. The core ideas of this research are accessing a repository of data and analyzing the resources found within. This research qualifies as archival due to us not creating new data nor running new experiments. The BLS maintains and updates the archive of employment statistics, and the repository remains open to public access through their website.

Cursory Trend Analysis

The aim of this archival research is to access the data repository that BLS has created and maintained. An analysis of this data will occur, followed by the creation of a predictive model that uses ARIMA data mining methodologies to forecast future values of CES data. The cursory analysis will document surface level trends within the data and document various surface-level statistics.

Predictive Model Creation

After the initial analysis, I will attempt to use ARIMA methodology to create an effective predictive model for the future of CES data. The model will be tested and analyzed to assess accuracy and validity. Publication of model creation and assessment methods will follow to increase the reproducibility of the analysis. I will compile and compare variations of the ARIMA methodology to determine which variation will produce the most accurate and valid results. These variations will be tested by comparing Akaike Information Criterion and Bayesian Information Criterion values.

Research Questions

This project will attempt to answer the following questions.

- What are the overarching trends within the state CES data?
- How do data mining methodologies, such as ARIMA, create valid models for measuring and predicting future CES data values?
- What variant of ARIMA analysis is optimal for CES analysis?

Setting

The setting of this paper is the business environment of the state of California. The scope of the data set for this analysis is limited to the state of California. The congregation of California's CES data originates from the entirety of California businesses that have published responses to the CES survey. The historical record of Californian CES data begins in 1990 and extends through 2023. The analysis of this data will occur from January 2024 to April 2024 using R. CES data for California is publicly available and was obtained legally from the Bureau of Labor Statistics and California Employment Development Department databases (accessible through their respective websites).

Participants

The participants in the CES survey are businesses within California. Participation in the CES survey is voluntary, and the resultant CES data is anonymized prior to publication. At no point within the CES data process are individuals' personally identifiable information made available to public users.

Data Collection

Every month, a CES survey is sent to a sample of businesses within California. BLS contacts businesses through phone, mail, or email (Bureau of Labor Statistics, 2023). Businesses report employment, hours worked, and earnings for that month's payroll period. This reported data encompasses all employees within the company (Bureau of Labor Statistics, 2023). The reporting process can occur through mail, email, or through a web-based reporting platform.

After reporting, BLS employees review the employment data to ensure accuracy and consistency. If discrepancies exist in the reported data, BLS employees communicate with the companies to clarify any potential issues (Bureau of Labor Statistics, 2023). For nonrespondent organizations, BLS uses various statistical methods to estimate the missing data based on historical trends and the data of similar businesses (Bureau of Labor Statistics, 2023). After recording and estimation, BLS uses seasonal adjustment methods to remove the effects of seasonal variation. BLS publishes a monthly report containing the aggregated data on the BLS web database.

Data Analysis

Regional Trend Analysis

Microsoft Excel will be used as data visualization software to create graphs that highlight the surface level trends present within each division of the Californian CES data. These preliminary analyses will include the summation and documentation of the summary statistics. These trends will then be analyzed against one another to determine any significant differences between the trends for various regions. Should differences present themselves, statistical methods will be used to analyze the various trends to determine if regional trends are significantly different from one another. This will be tested through a combination of traditional statistical tests (such as T-tests or ANOVA) and more complex statistical methods such as cross-correlations and correlation analysis. The results from these analyses will be published into chapter 4, where further discussion takes place.

Predictive Model Creation

The development of a predictive model shall follow the surface-level analysis. Methods to create predictive models for time series data (including ARIMA, Seasonal ARIMA, and Exponential Smoothing Methods) will occur. These methods facilitate the creation of a predictive model for time series data. Furthermore, the seasonal variations of ARIMA methodology allow for the analysis of both seasonally adjusted and non-seasonally adjusted CES publications. Afterwards, I will test the validity of the created model to determine the accuracy and functionality of a created predictive model for CES data using diagnostic checking and residual analysis methods. R scripts will be used as the primary software to handle the computations required to create the ARIMA model. After creating multiple ARIMA models, the goodness-of-fit measures for each model will be compared, and an ideal model will be identified,

Validity

Testing the validity and accuracy of the analysis will occur after model creation. Diagnostic checking methods allow researchers to examine the residuals within the data to ensure they do not significantly deviate from the assumptions of the data. Further, the data for ARIMA analysis will be split into a training partition and a testing partition. The model created by the training partition will be tested for validity against the testing partition. In forecast evaluation, metrics including mean absolute error (MAE), root mean squared error (RMSE), and mean squared error will be used to assess the validity of created models.

Conclusion

The methodologies will provide valuable information when applied to the set of CES data. The value of trend analysis will allow me to observe various trends that provide insights into the overall trends present within the divisions of CES data. Looking forward, the results of the applications of these methodologies will be documented into chapter 4.

CHAPTER 4: PRESENTATION OF THE FINDINGS

Before addressing the previously outlined research questions, I compiled the relevant data series from the BLS web database into a series of tables containing the data for each sector of the workforce identified by BLS. These sectors include total nonfarm, total private employment, total good-producing, total service-providing, private service-providing, mining and logging, construction, manufacturing, trade and utility, information, finance, health, hospitality, and governmental employment. For all sectors of the workforce, data indicating the total measure of employment through the number of employees of a given industry exists. For some sectors of the workforce, data indicating the average weekly work hours, hourly earnings, and weekly earnings exist. The exact varieties of data used for each sector of the workforce analyzed for this experiment can be found in Table 1.

There exist intentional design trends within the designations of workforce sectors. Each sector identified by an ID ending in 0 (10, 20, 30, etc.) sums the various data series between that series and the next series ending in 0. For example, sector 30, Manufacturing, aggregates all data in sectors 30 through 39. Furthermore, data series 00, total nonfarm, aggregates all available CES data from all data series.

Data Analysis

The analysis of this data occurs in three phases. First, an entry-level analysis of California's CES data will occur, with the intention of identifying overarching facts about California's economy. Secondly, ARIMA models will be created to demonstrate the viability of ARIMA methodology on CES data. Lastly, the competing ARIMA models will be compared to determine which ARIMA model performs optimally in forecasting future values of CES data.

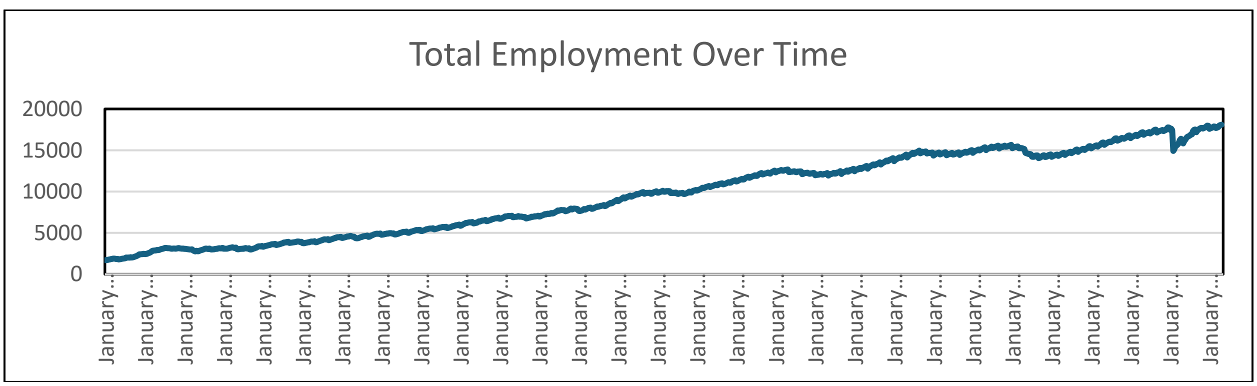

Figure 2: Total Employment Over Time

Cursory CES Analysis

Visualizing the relation between the change of total employment over time as a line graph creates Figure 1. Within Figure 1, various traits about the employment statistics become observable. Numerous time periods that deviate from the trendline exist. While these time periods represent major economic events, the cause of these events fall beyond the scope of this project. Notably, a substantial positive trend presents itself within the data, shown in the significant increase in total employment from 1939 to 2023. Performing regression analysis on total employment over time provides a statistical analysis of the positive trend revealed through observation in Figure 1. The results of the regression analysis are found in Tables 2 and 3.

Table 1: Regression Statistics for Total Employment

Regression Statistics	
Multiple R	0.992187672
R Square	0.984436377
Adjusted R Square	0.984421089
Standard Error	612.7892243
Observations	1020

Table 2: ANOVA and Regression Analysis Results

ANOVA	*df*	*SS*	*MS*	*F*
Regression	1	2.4179E+10	2.42E+10	64390.93617
Residual	1018	382269825	375510.6	
Total	1019	2.4562E+10		

REGRESSION	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	1215.126835	38.3461506	31.68837	6.8215E-154
Time Period	16.53537557	0.06516309	253.7537	0

Analysis of the results of the regression model shows the accuracy of the regression equation. Within the regression statistics, the high adjusted R-Square value indicates that the generated regression equation sufficiently manages 98.44 percent of the variation within the total employment data series. The high F value in the ANOVA block, in addition to the low Significance F and P-values indicate that the regression equation accurately and significantly reflects the current values of total employment. For ARIMA analysis, this indicates that the data of total employment over time has nonstationary properties. In addition to understanding stationarity, understanding the seasonality of employment data is crucial for generating an appropriate ARIMA model.

For the purposes of ARIMA analysis, understanding whether the underlying data exhibits seasonal variations determines whether ARIMA or SARIMA methodologies provides a model that more accurately represents the underlying data. Removing the trend component of a time series through differencing enables the observation of the seasonal component present within the time series and determine the presence of seasonal trends within the data.

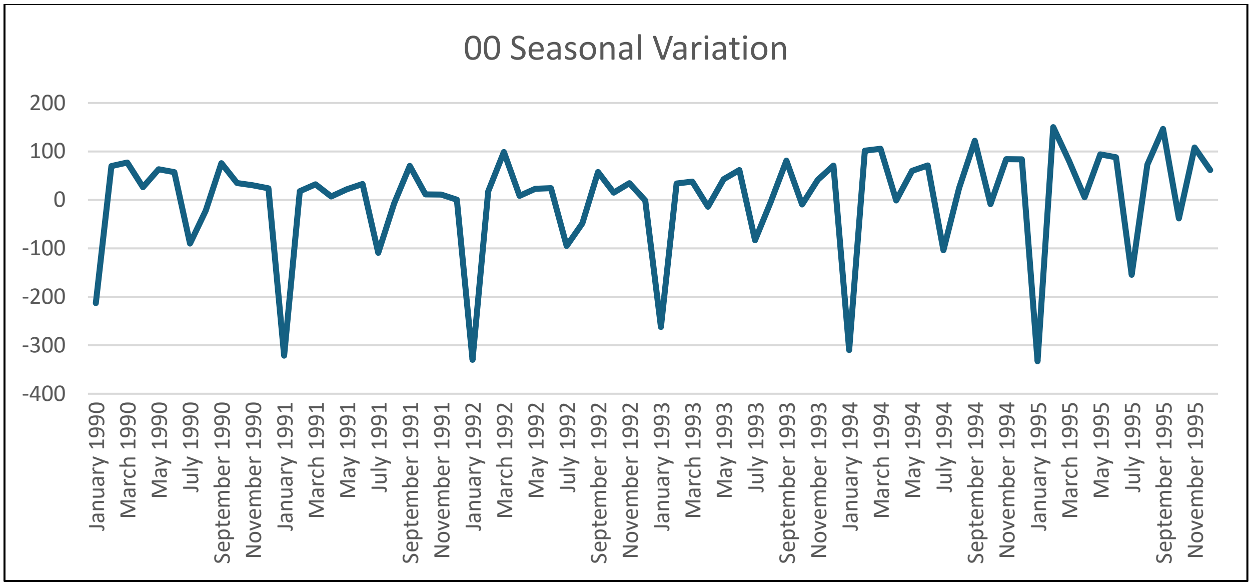

Figure 3: 00 Series Seasonal Variations

Applying differencing to the total employment data enables the visualization of the seasonal variation present within the total employment data series. The results of this visualization exist in Figure 2. Within Figure 2, three noticeable trends appear. Firstly, a severe drop in employment occurs every year within the January CES report. Secondly, a smaller significant drop in employment occurs every year during July. Thirdly, after each significant drop in employment during July and January, next month's report shows employment returning to previous levels. With the trend component of the underlying data removed, these trends present themselves clearly. As a result, we can say confidently that seasonal variations with the underlying data exist. Moving forward, this seasonality implies that the seasonal variations of ARIMA methodology will more accurately model the trends present within the underlying data.

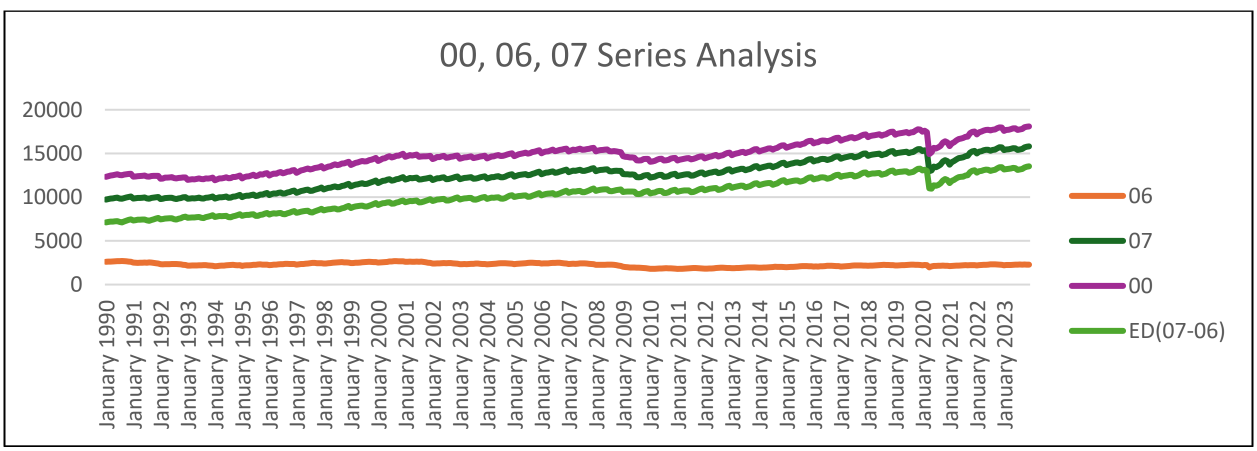

Figure 3: A line graph of data series 00, 06, and 07 over time

Understanding the internal divisions of data within a time series provides insight to the underlying trats of a dataset. A display of data series 05, 06, 07, and 07in a line chart in Figure 3 reveals the discrepancy between service-providing and goods-producing businesses within

California. Within this graph, multiple observable trends arise. Firstly, goods-producing industries have not experienced observable growth since the origin of CES data collection. Secondly, goods-producing industries by inspection do not exhibit as much variation in total employment over time. Measuring the slope of the Euclidean Distance (ED) between series 07 and 06 shows that series 07 and 06 exhibit significantly different trends over time. Moving forward to ARIMA analysis, it is reasonable to hypothesize that model performance will yield similar results for both total employment data and private employment data.

Overall, this analysis of California's total employment indicates that California has maintained a constant state of economic growth since the origin of CES data collection. While this analysis provides valuable insight into the overall economic state of California, further analysis of the individual data series within Californian CES data provides deeper observations of the economy. By understanding stationarity, seasonality, and other general traits of the underlying data, creation of an appropriate ARIMA analysis is possible.

Creation of ARIMA Predictive Models

The programming language R contains the necessary tools to create and compare the performance of competing ARIMA models. Moving forward, all analyses were performed using R Statistical Software (v.4.3.3; R Core Team, 2024). Completing the ARIMA analysis within R requires the utilization of various software packages available through the Comprehensive R Archive Network (CRAN). The "Tidyverse" package provides various utilities that assist in the coding of R scripts. Most importantly, Tidyverse allows researchers to access the individual variables within a data structure independently in a global environment, which enables easy access to ARIMA model performance metrics (Wickham et al, 2019). The "Tseries" package provides functionality for arranging data from external files into time series objects, which can then serve as input for various model creation methods. Furthermore, Tseries provides tools within R to create graphs, plots, and summary information utilizing the inputted data (Trapletti & Hornik, 2018). The "forecast" package provides functionality to create state space modeling functionality for time series including ARIMA modeling (Hyndman et al, 2024). These three packages collectively provide the utility to import data, use the data to create a time series, and perform ARIMA model creation and analysis on the time series.

```
1  library(forecast)
2  library(tseries)
3  library(tidyverse)
4
5  employmentData <- read.csv("C:/Users/Borseph Babbabs/Desktop/Thesis R Scripts/00 NSA Series.csv
6
7  tsemployment <- ts(data = employmentData['Value'], start = c(1939,1), frequency = 12)
8
9
```

Figure 4: The beginning of the R scripts used for analysis.

All the R scripts used for analysis contain the same initial lines of code displayed within Figure 4. Lines 1-3 import the libraries of the forecast, tseries, and Tidyverse packages. These statements enable the use of the necessary tools for the analysis within the script. Line 5 of the script contains the read.csv method, which allows the script to read the contents of a csv file and store the contents within an R data frame object using a file path to the data as a parameter. Line

7 shows the time series object constructor with several parameters. The data parameter references the data frame object containing the employment data, the start parameter identifies the date of the first data point, and the frequency parameter identifies the monthly nature of the data. After these initial steps, ARIMA analysis can occur. Figure 4 exemplifies the necessary code to create an ARIMA model out of a time series object.

The ARIMA constructor (Seen in lines 17-19) in R serves as the primary method of ARIMA model creation within R. The ARIMA constructor has several vital parameters that determine the model's performance. The first parameter, data, identifies the time series object that the ARIMA object will model. The order parameter uses a vector variable to represent the ARIMA model parameters p, q, and d. In the same manner, the seasonal parameter identifies the seasonal SARIMA parameters P, Q, and D. The Period parameter determines the frequency of seasonal variations, and the method parameter determines the fitting method for the ARIMA model. By setting all of these values, a precise ARIMA model is created.

```
15 #build the ARIMA model
16 #SARIMA(1,0,0) (1,0,0)
17 sarima100100 <- arima(tsemployment, order = c(1,0,0),
18                       seasonal = list(order = c(1,0,0), period = 12),
19                       method = "ML")
20 AIC(sarima100100)
21 BIC(sarima100100)
22 sarima100100
```

Figure 5: Example code for creating an ARIMA model in R.

After creating the ARIMA model, the researchers will retrieve and analyze various performance metrics. Line 20 retrieves the AIC for the provided ARIMA model. Line 21 retrieves the BIC for the provided ARIMA model. Line 22 prints a summary of the ARIMA model including order, coefficients for each variable used in the analysis, and the standard error of each analysis variable. Analyzing these metrics of model performance enables comparison of competing models, and the capability to determine the optimal model.

Identification of Optimal ARIMA Model

After creating a given ARIMA model, an assessment of the model's performance must occur. Two main measures are used to judge model performance: the Akaike Information Criterion(AIC) and Bayesian Information Criterion(BIC). The optimal model will minimize both AIC and BIC values. However, due to the sheer number of SARIMA parameter values, we must narrow the scope of potential parameter values to identify which SARIMA variations will not fit the data.

Identifying the optimal ARIMA model necessitates the comparison of all competing variations of ARIMA parameters. Due to the characteristics discussed within the cursory analysis, we can narrow the range of potential ARIMA variations. Due to the identification of a seasonal component, we can limit potential models to all SARIMA variations. Furthermore, the identification of a first-order trend component narrows the scope to all SARIMA models with a q value of 1. The lack of a trend component within the seasonal variation of employment determines that the seasonal P parameter will be 0. With these parameters identified, we can begin to compare the performances of various SARIMA variations. Comparison of competing SARIMA models will use AIC and BIC parameters to identify the optimal models.

```
       Estimate Std. Error  z value  Pr(>|z|)
ar1   0.0940864  0.0311432   3.0211 0.0025187 **
ar2  -0.1170789  0.0311331  -3.7606 0.0001695 ***
sar1  0.9930962  0.0029122 341.0105 < 2.2e-16 ***
sma1 -0.8773188  0.0155266 -56.5044 < 2.2e-16 ***
```

Figure 6: Significance Analysis of SARIMA(2,1,0)(1,0,1)

Observing the distinct performance values for each SARIMA variation in Table 4 reveals that SARIMA(2,1,0)(1,0,1) minimizes both the AIC and BIC values, which indicates that this variation performs optimally among all other variations. With the identification of the optimally performing model, we can now more thoroughly assess the performance of the model through an analysis of significance and an analysis of the residuals.

The significance analysis results can be found in Figure 6. The significance test determines if each SARIMA parameter significantly impacts the overall performance of the model. The test for significance runs against the null hypothesis assuming the insignificance of each parameter. The low Pr values for each parameter indicate that all levels of all parameters for the SARIMA(2,1,0)(1,0,1) model maintain significance in overall forecasting strength. Furthermore, the significance of all parameters indicates the degree of model accuracy for forecasted values.

The residual analysis results reside in Figures 7 and 8. Residual analysis provides vital information regarding the general validity of the ARIMA model. If the residuals of an ARIMA model contain a significant level of autocorrelation, then the ARIMA model proves to be invalid. A Ljung-Box Test determines whether the residuals of an ARIMA model contain significant autocorrelation. A p-value greater than 0.05 states that the autocorrelation within a given set of residuals does not have significance. Figure 7 shows that the Ljung-Box Test returns a p value of .1549, which indicates that the residuals of the ARIMA model do not contain significant Autocorrelation. Plotting the residuals in figure 8 reveals that a significant portion of the variations within the residuals stems from the large shifts in total employment from January 2020 to June 2020. This observation, in addition to the results of the Ljung-Box Test confirms that the variation within the residuals stems from white noise and random variation.

```
        Ljung-Box test

data:  Residuals from ARIMA(2,1,0)(1,0,1)[12]
Q* = 26.338, df = 20, p-value = 0.1549

Model df: 4.   Total lags used: 24
```

Figure 7: Ljung-Box Test results for SARIMA(2,1,0)(1,0,1)

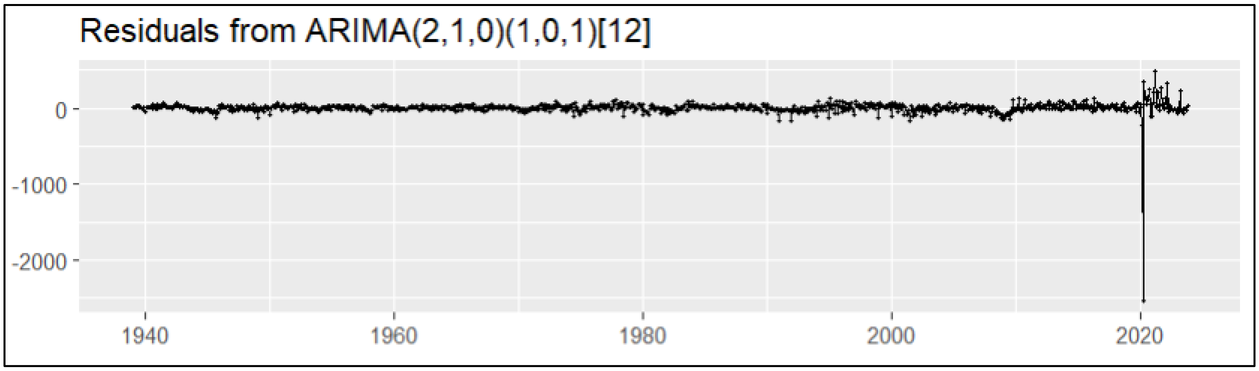

Figure 8: A plot of the residuals from the SARIMA(2,1,0)(1,0,1) model

Relations between findings and Research Questions

The cursory analysis of CES data revealed multiple significant factors. Firstly, the regression equation created to model total employment identified a statistically significant trend component, which reveals the non-stationary aspect of CES data. Breaking down total employment into service-providing and goods-producing industries reveals that the trend component of the data is not present within the goods-producing industries of California. Meanwhile, the service producers of California have thrived and increased greatly over time. By applying first-order differencing to total employment, we can isolate and identify the characteristics of the seasonal variations within total employment. In this process, three notable variations arose. Underlying factors such as seasonality, stationarity, trend, and data components have significant impacts on an ARIMA model's performance. As such, understanding these factors provides substantial utility for the purposes of ARIMA model creation and optimization.

R can facilitate the creation of ARIMA and SARIMA models using the forecast package. The data wrangling process for ARIMA model creation involves importing the data, transforming the data into a time series, and using the time series as the input for a SARIMA analysis object. The highly available and open-source nature of R and CRAN packages determines that this process can easily be replicated. Furthermore, documenting a standardized process for model creation limits the sources of human errors during model comparison. The identification and analysis of the optimal ARIMA model lets us determine if the optimal ARIMA accurately models the underlying data and matches the assumptions made by the underlying data.

Discussion

Residual analysis and coefficient analysis of the SARIMA(2,1,0)(1,0,1) model confirm that the SARIMA model fits the underlying employment data in an accurate and significant manner. Ensuring the model's accuracy provides credit to the ARIMA creation process and the applications for ARIMA modeling for CES data. However, there are some characteristics regarding ARIMA model creation for total Californian employment that demand acknowledgment. Firstly, within the scope of Californian CES data today, only the total employment series contains data dating back to 1939. Most other data series for California begin in 1970. This means that the earlier portions of total employment must be discarded for research comparing total employment series. However, ignoring total employment data from 1939 to 1970 can negatively impact the model's overall performance.

Summary of the Findings

Through the process of ARIMA model creation, comparison, and analysis, a SARIMA(2,1,0)(1,0,1) model optimally represents the variations in total employment. After identifying an optimal model, verification of the model's performance occurs through the methods of coefficient analysis and residual analysis. With an optimal model established, future values of total employment can be generated.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary and Discussion

Above, we created numerous ARIMA models to determine the optimal ARIMA for CES forecasting. Overall, this project fills a niche in the field of employment analysis by applying ARIMA methodology to a previously unutilized dataset. Further information on the project's performance, impact, and framework is published below.

Study Results

Comparing the performance metrics of numerous ARIMA models reveals that a SARIMA(2, 1, 0)(1, 0, 1) model optimally forecasts future CES values compared to other variations of ARIMA modeling. Analysis of this model through the use of Coefficient Analysis, Ljung-Box Testing, and Residual Analysis determined that the ARIMA model encompasses all significant factors of change within the data, and that the residuals of the model are not autocorrelated, which implies that the variance not accounted for by the model is due to random variance, as opposed to unaccounted trends.

The analysis of the created ARIMA model forms two major conclusions regarding the applications of ARIMA methodology on CES data. Firstly, the coefficient analysis determines that the generated ARIMA model accurately captures most of the total variation between CES observations. The residual analysis implies that the uncaptured variation within the data does not stem from an underlying weakness within the predictive model. This implies that ARIMA methodology can create valid and accurate models of employment data.

Impact on the Field of CIS

Analysts and other professionals seeking to better understand the underlying trends of employment in their region can follow the same ARIMA modeling process demonstrated within this study to create a model that assess the trends of employment for their region. Furthermore, the understanding that ARIMA modeling processes produce valid and accurate models for CES data can lead to other researchers utilizing ARIMA methodologies to discover deeper trends within CES data or other BLS databases.

Objectives

This research sought to determine the validity of ARIMA modeling employment data to forecast future values and trends of employment in California. During this process, the model creation, optimization, and analysis processes were documented to increase the repeatability of the research, and to allow readers to use this process to model various subsets of employment data for their own purposes.

Conceptual Framework

The demonstrated research furthers the endeavors of both employment analysis and ARIMA modeling by applying the ARIMA methodology to CES data. Furthermore, the study of CES data can be replicated to allow other third parties to discuss and understand the trends present within employment data. The validity of ARIMA modeling of employment data was previously unknown, and this research establishes a precedent of validity for employment ARIMA modeling.

Strengths

The sheer amount of source data provides significant strength to the model created within this research. Furthermore, the source data for the model maintains predictable patterns in both the trend and seasonal components, which makes the source data favorable to ARIMA modeling. Furthermore, the source data does not exhibit any long-term dependencies between the dependent and independent variables.

Limitations

The core limitation of this model, and ARIMA modeling, is that the model created in this research can forecast future values of the data used to train the model exclusively. Any changes within the source data necessitates the retraining of the ARIMA model.

Additional Findings

During the initial data analysis of the employment time series, we showed that the goods-producing industries of California have not experienced any significant shift in total employment over time. This discovery highlights two distinct implications for further analyses. Firstly, total goods-producing employment has remained static over time, but the distribution of employment among goods-producing industries can change over time, which can be traced using additional analyses. Similarly, an analysis of service-providing industries can reveal which industries contain the largest portions of the trend component of total employment.

Recommendations for Action

Professional analysts can create their own models to monitor changes within their geographic region and work sector to understand the employment trends within their industry. These models also allow companies to assess the state of the industry more accurately, which can be further extrapolated to understand the economic position of the company and its competitors. Creating an independent model also verifies the validity and accuracy of modeling techniques applied to employment data.

Recommendations for Further Study

Below, we highlight two major recommendations for further study into the application of ARIMA modeling of employment statistics. Firstly, a horizontal study which models and monitors the changes within a single industry or sector across multiple geographic regions and compares the created models to determine if the geographic regions exhibit the same trends and influences within the same sector. Secondly, a vertical study that models and analyzes multiple work sectors within the same geographic region that seeks to understand and explain the similarities and differences between the trends present in each industry.

Conclusion

Overall, this project demonstrates the ability of ARIMA methodology to model and forecast data regarding employment in California. The documentation and analysis of this study allow readers to recreate this process for other data sets to highlight specific trends within individual work sectors and geographic region. While issues potentially arise due to significant deviations and variations within the data due to world events, the sheer amount of CES data available bolsters the model to demonstrate the creation of an effective model that forecasts the future of employment.

TABLES AND FIGURES

Table 3: BLS Workforce Sector Information

Sector ID	Sector Name	Available Data Series
00	Total Nonfarm	Total Employment
05	Total Private	Total Employment
06	Total Goods-Producing	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
07	Total Service-Providing	Total Employment
08	Total Private Service-Providing	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
10	Mining and Logging	Total Employment
15	Mining, Logging, and Construction	Total Employment
20	Construction	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
30	Manufacturing	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
31	Durable Goods	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
32	Non-Durable Goods	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
40	Trade, Transportation, and Utilities	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
41	Wholesale Trade	Total Employment
42	Retail Trade	Total Employment
43	Transportation and Utilities	Total Employment
50	Information	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
55	Financial Activities	Total Employment, Average Weekly Hours, Average Hourly Earnings, Average Weekly Earnings
60	Professional and Business Services	Total Employment, Average Weekly Hours, Average Hourly Earning, Average Weekly Earnings
65	Education and Health Services	Total Employment, Average Weekly Hours, Average Hourly Earning, Average Weekly Earnings
70	Leisure and Hospitality	Total Employment, Average Weekly Hours, Average Hourly Earning, Average Weekly Earnings
80	Other Services	Total Employment, Average Weekly Hours, Average Hourly Earning, Average Weekly Earnings
90	Government	Total Employment

Table 4: The AIC and BIC values for SARIMA variations

SARIMA Variation	AIC	BIC
SARIMA(2,1,0)(1,0,0)	12457.62	12477.33
SARIMA(3,1,0)(1,0,0)	12458.95	12483.58
SARIMA(1,1,1)(1,0,0)	12465.13	12484.84
SARIMA(2,1,1)(1,0,0)	12458.71	12483.34
SARIMA(3,1,1)(1,0,0)	12460.7	12490.26
SARIMA(1,1,0)(2,0,0)	12362.47	12362.47
SARIMA(2,1,0)(2,0,0)	12350.78	12380.4
SARIMA(3,1,0)(2,0,0)	12353.42	12382.98
SARIMA(1,1,1)(2,0,0)	12356.96	12381.59
SARIMA(2,1,1)(2,0,0)	12353.56	12383.12
SARIMA(3,1,1)(2,0,0)	12355.44	12389.92
SARIMA(2,1,0)(2,0,1)	12161.63	12191.19
SARIMA(3,1,0)(2,0,1)	12161.65	12196.14
SARIMA(2,1,1)(2,0,1)	12162.26	12196.75
SARIMA(1,1,0)(1,0,1)	12171.98	12191.69
SARIMA(2,1,0)(1,0,1)	12159.93	12184.57
SARIMA(3,1,0)(1,0,1)	12160.06	12189.62
SARIMA(2,1,1)(1,0,1)	12160.62	12190.18
SARIMA(3,1,1)(1,0,1)	12160.67	12195.16
SARIMA(2,1,0)(3,0,0)	12298.02	12327.58
SARIMA(3,1,0)(3,0,0)	12299.42	12333.91
SARIMA(2,1,1)(3,0,0)	12299.57	12334.06
SARIMA(3,1,1)(3,0,0)	12300	12340.37

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IDENTIFYING THE EFFECTIVENESS OF DIGITAL PLATFORM BASED TRAINING IN THE WORKPLACE: RELATIONSHIPS AMONG TRAINING EVALUATION CRITERIA

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ABSTRACT

This study aims to identify the positive relations among training criteria including reaction, learning, job performance, and organizational impact in digital platform-based training programs. To answer the research questions, this study will collect the previous studies associated with digital platform-based training programs such as e-learning, online learning, mobile learning, and learning management system training in organizations and conduct a meta-analysis. A summary of the searching and screening process based on a PRISMA flow diagram will be demonstrated. This study will contribute to theories in the field of employee training development and teaching and corporate digital training platforms. Methodologically, this study serves as an example of how meta-analysis can be used to synthesize previous studies of business information system topics. Practically, the results of the research will provide human resource development practitioners in the organizations with further direction on how to identify the effectiveness of digital platform-based training in the workplace.

Although both private and non-profit organizations have attempted to change a type of training program from classroom to digital platform driven learning (e.g., e-learning, online learning, mobile learning, and so on) after COVID-19, many human resource development (HRD) managers and practitioners seem to be reluctant to adopt digital platform based training programs. They may have difficulty providing stakeholders with evidence for digital platform based training programs' contribution to enhancing organizational performance.

Donald Kirkpatrick's four-level training evaluation model (Kirkpatrick, 1959a, 1959b, 1960a, 1960b) has been easily understood and become the most influential and prevalent one in the field of employee training and development (Alliger & Janak, 1989; Alliger et al., 1997). Kirkpatrick argues that training can be evaluated using four criteria or levels of evaluation: reaction, learning, job performance, and organizational impact (Kirkpatrick & Kirkpatrick, 2006). According to Alliger and Janak (1989), one of the questionable assumptions about the training criteria of a four-level training evaluation model by Kirkpatrick is that they are causally linked and positively intercorrelated. Following the assumption, HRD scholars and practitioners have promoted that positive reactions encourage effective learning, and this learning can contribute to behavioral changes and ultimately improve organizational results (Alliger & Janak, 1989; Hilbert et al., 1997; Kirkpatrick & Kirkpatrick, 2006). In other words, as long as the significance of the positive relations among criteria is demonstrated, researchers and professionals can estimate the effectiveness of job and organizational performance only with results from level 1 (reaction) and 2 (learning). Indeed, the most commonly gathered training criteria are trainee reactions (Bassi et al., 1996; Saari et al., 1988) because they are easy to be collected than the other levels. In addition, previous research has addressed that level 2 (learning) is the most popular level adopted to measure training programs even though some studies do not advocate equivalence between learning and job performance (Reio et al., 2017; Strunk, 1999). Thus, if such a relationship is empirically proved, the reaction and learning evaluation of the digital platform based training program may be sufficient to replace the measurement of effects on behavior and organizational performance.

Despite the significance of the relations among the training criteria, there have been few synthetic studies on identifying the relations about digital platform based training programs. Although many scholars have adopted alternative evaluation models that are similar to and different from a four-level training evaluation model (e.g., Bushnell, 1990; Holton, 1996; Phillips, 1999, 2003; Russ-Eft & Preskill, 2005; Swanson, 1994), there is a limit to the lack of empirical evidence on them. Therefore, this study aims to identify the positive relations among training criteria including reaction, learning, job performance, and organizational impact in digital platform based training programs. Thus, the research question for this study is: *What are the correlation between reaction and learning, and job and organizational performance? How do participants' positions and types of interventions (training contents) moderate these relationships?*

To answer this question, I will collect the previous studies associated with digital platform based training programs such as e-learning, online learning, mobile learning, and learning management system training in organizations and conduct a meta-analysis. Before gathering data, in order to search for primary research and avoid missing a valuable paper related to the topic of this study, four search strategies will be adopted in order: consultation, searches in subject indexes, browsing, and citation search. In addition, in order to acquire transparency and replicability of this study, I will establish eligibility criteria for several dimensions such as population, research methodology, learning type, evaluation criteria, and research model with the statistical result. A summary of the searching and screening process based on a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al., 2009) flow diagram will be demonstrated. After coding variables and information, I will conduct statistical analyses to examine missing data, effect sizes, publication bias, outliers, and meta-regression for moderators.

The results of this meta-analysis will reveal the relationships between reaction and job performance, and learning and job performance from the evaluations of digital platform based training programs in the workplace on the ground of Kirkpatrick's four-level training evaluation model. This study will contribute to theories in the field of employee training development and teaching and corporate digital training platforms. Methodologically, this study serves as an example of how meta-analysis can be used to synthesize previous studies of business information system topics. Practically, the results of the research will provide HRD practitioners in the organizations with further direction on how to identify the effectiveness of digital platform based training in the workplace.

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ASSESSING THE IMPACT OF COMPUTER-BASED INTERRUPTIONS ON TASK PERFORMANCE AN EYE-TRACKING EXPERIMENTAL STUDY

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ABSTRACT

Interruptions are always occurring in the business working environment and can be annoying for workers. More importantly, interruptions can significantly delay task completion time, increase error rates, and create disruptions in the workflow. Our study investigates the effect of controlled computer-based interruptions on task completion time by utilizing an eye-tracking experimental study. Data analysis based on analysis of variance (ANOVA) on a sample of 76 participants provided significant evidence for the negative effect of computer-based interruption on task completion time.

Key Words: Computer-Based Interruptions, Eye Tracking, Behavioral IS Research, Experimental Study, and Working Efficiency.

INTRODUCTION

In the working environment, interruptions are ubiquitous, leading to problems in various business settings. Research shows that work interruptions have a significant impact on the workplace across various aspects. Studies have investigated the effects of interruptions on work processes, including task completion time and error rates. It has been found that frequent interruptions can lead to delays in task completion, increased errors, and disruptions in the workflow. Furthermore, research has highlighted the impact of interruptions on concentration and cognitive load. Interruptions lead to increased cognitive load, making it difficult to re-concentrate on primary tasks, ultimately affecting the quality of work and working efficiency. As productive workers, we are expected to handle these distractions effectively. However, as humans, we are not always adept at multitasking, and switching our attention between tasks can be challenging and inefficient. Therefore, understanding the influence of interruptions and effectively managing them can enhance our working efficiency.

LITERATURE REVIEW

Distraction

Distraction is defined as “something that diverts attention away from an ongoing” (Baron & Kenny, 1986, p.4). The “ongoing” is the primary task, while all other tasks are regarded as secondary. When a secondary task is unrelated to the primary task, it becomes a distraction. For example, in the use of an information system, users may encounter additional information while processing data for their primary task. Processing this additional information becomes a secondary task. If the additional information does not contribute to the completion of the primary task, it is a distraction. Distractions can arise from the specific systems used to carry out the current task. For example, while composing an email, an unrelated email might pop up and distract the user. Distractions can also originate from other systems. For example, during work, pop-up notifications from social media may divert users' attention.

According to some researchers, attention is considered a singular resource(Kahneman, 1973). Users switch their focus between the primary task and the distraction because only one stimulus can be attended to at any given moment (Jeong & Hwang, 2012). Dual-task interference theory (DIT) indicates that the human brain faces difficulty in simultaneously handling multiple tasks without experiencing a significant decline in overall performance, even if the tasks are straightforward (Jenkins et al., 2016). The distraction effect can cause the user to put the primary tasks aside and instead engage in irrelevant activities. In this case, the user deals with the primary task and the distraction task consecutively. The users' attention is shifted away from the primary task to the distractive information, which results in the primary task's completion being delayed. Meanwhile, there are contrasting views from other researchers who propose that attention involves multiple resources that can be allocated simultaneously to different tasks. This perspective is elaborated upon by the multiple resource theory (Gupta & Irwin, 2016) and threaded cognition theory (TCT) (Salvucci & Taatgen, 2008).

Distractions are frequently linked to cognitive failures(Hadlington & Murphy, 2018; Magen, 2017). In the context of texting while driving, the distraction effect leads drivers to perceive lower levels of risk, which, in turn, prompts them to engage in more potentially hazardous behaviors (Gupta & Irwin, 2016). Also, research shows that the distraction can negatively impact working memory accuracy(Zickerick et al., 2020). Beside those negative influences, distractions can yield positive outcomes. Individuals may not realize that they are multitasking when they do. In some case, people enjoy multitasking(Czerwinski et al., 2004; Forsberg et al., 2015). Also, researchers have discovered beneficial effects of distraction, particularly in the context of background music (Blood & Zatorre, 2001; Gefen & Riedl, 2018). When individuals are exposed to background music that is unrelated to their main task, the music becomes a form of distraction. Background music do influence decision-making by enhancing people's pleasure(Blood & Zatorre, 2001)and reducing customer dissatisfaction during waiting periods(Peevers et al., 2009). Additionally, studies have shown that background music can enhance the attention given to advertising messages (Gefen & Riedl, 2018). However, it is essential to note that most of these positive effects do not directly relate to the performance of the primary task.

The impact of distractions varies from person to person, as individuals differ in their susceptibility to them. Certain individuals are less prone to reactance than others (Drews & Musters, 2015). These individuals are likely to restrict their ability for rational reasoning and perceive threat to the feeling of freedom. When they are confronted with distraction, they may view it as an attempt to manipulate or control them, leading them to disregard it.

Interruption

Interruption is a specific type of distraction. An interruption is an externally generated, random event that disrupts the cognitive focus on the primary task (Coraggio, 1990, p.19). These interruptions typically demand immediate attention and action (Covey, 1989, pp. 150–152). Interruptions have two key characteristics: 1, these are unexpected. 2, these lead to the immediate suspension of the current task. In the area of human computer interaction, interruption is defined as “the process of coordinating abrupt changes in people’s activities”(McFarlane & Latorella, 2002) In this definition, four elements are involved, including “(P) the people involved in the interruption; (T) the task(s) the person is attempting; (In) the interruption itself; and (C) the working context or environment” (McFarlane, 1997, p. 4).

The interruption involves unexpected events occurring during the primary task, like receiving an email(Addas & Pinsonneault, 2018), a systems alert notification(Jenkins et al., 2016), a security warning(Vance et al., 2018), or other notifications (Paul et al., 2015). Additionally, interruptions can also arise when the system experiences lag(Altmann & Trafton, 2015)or becomes temporarily unusable(Hodgetts et al., 2015). When interruption diverts a user's attention, it causes delays in completing the primary task, increasing the overall cognitive processing load, and potentially influencing the quality of the primary task.

Studies proposed a model to describe the process of interruptions, which unfolds in a sequential manner(Trafton et al., 2003; Weng et al., 2017). According to the model, the interruption occurs in a time sequence comprising three stages. First, a distractor triggers the interruption, diverting the person's attention away from the primary task. Subsequently, the individual attends to the interruption, addressing or processing it. Finally, after the interruption has been handled, the person resumes the primary task. Within this process, two distinct lags are identified. The first is the interruption lag, which refers to the duration between the initial occurrence of the interruption and the moment when the person begins to deal with it. The second is the resumption lag, representing the time span between the conclusion of the interruption and the recommencement of the primary task (Weng et al., 2017). In 2015, Addas and Pinsonneault conducted a study on IT interruption, focusing on the relevance of content to primary tasks (i.e., whether it is relevant or irrelevant) and the content structure (i.e., whether it is informational, actionable, or system-related). In a subsequent study, they further classified 36 interruptions into two groups: congruent and incongruent (Addas & Pinsonneault, 2018). The term "congruent" indicates that the distractor is related to the primary task but does not directly impact its execution. On the other hand, "incongruent" refers to a distractor that is unrelated to the primary task. The study revealed that when the distractor is relevant to the primary task, it indirectly influences mindfulness in a positive manner. However, if the distractor is irrelevant to the primary task, it negatively affects the workload (Addas & Pinsonneault, 2018).

Attentional and working memory are crucial to efficiently handle interruption. Working memory run control functions, by inhibiting irrelevant information and maintaining relevant information for a task(Baddeley, 2012). The process of selection the irrelevant and information, which support this control function, also drive away individuals’ attention (Gazzaley & Nobre, 2012; Sawaki et al., 2012). And in some situation, because of the increased demand for multitasking, it is not easy to determine what activity is secondary task, which support the primary task, and what activity is purely distraction of primary task(Baethge et al., 2015). This effect have been studied and described as bottom-up or stimulus-driven attention (Desimone, R., & Duncan, J., 1995)

Influence of Interruption

Prior research has revealed that interruptions lead to adverse effects, including reduced accuracy (Altmann & Trafton, 2015; Trafton et al., 2003), prolonged task completion time (Addas & Pinsonneault, 2018; Carayon et al., 2007; Hodgetts et al., 2015), and diminished performance quality in handling complex tasks (Paul et al., 2015; Speier et al., 1999). Since Interruption impairs the ability to process relevant information in working memory, the time for task completion is extended and the corresponding accuracy reduced (Sakai et al., 2002). When a task is interrupted, its completion time is prolonged by two transition time intervals: 1, interruption lag, which refers to the time taken to switch from the primary task to the secondary task, 2, resumption lag, which is the time required to return from the interruption task back to the primary task (Altmann & Trafton, 2002). As a result, the completion time over all is delayed. Other streams of research show that the interruption is associated with an increasing error rate. For example, Interruption is commonly seen in the daily activities of doctors in the medical field. Those distractions increased the errors rate and make it harder for doctors to back to their primary tasks (Mobeen et al., 2022).

Interruption could have harmful effect on the performance and well-being of individuals(Baethge et al., 2015). Literature shows that poorly timed notification can have negative impacts on workers' task performance and delay task completion. Additionally, recent smartphone use research point out that users perceive notification alerts as an interruption, which diverts their attention from their current task of driving an automobile(Caird et al., 2014; Törnros & Bolling, 2005). An early study demonstrated that receiving notifications with ringtone alerts may lead to symptoms of inattention and hyperactivity (Kushlev et al., 2016). Researchers have provided explanations for these detrimental effects of interruptions. For instance, Addas and Pinsonneault (2015) highlighted that interruptions from information technology (IT) sources can lead to information overload, burdening individuals with excessive data to process. Moreover, the time and effort required to handle interruptions have negative consequences on overall productivity(Addas & Pinsonneault, 2018).

In the workplace, individuals employ various strategies to cope with interruptions (Weng et al., 2017), which often results in the interruption being only partially addressed when they return to their primary activities (Addas & Pinsonneault, 2018). Due to our limited information processing capability, when the volume of information input surpasses our processing limitation, we experience information overload (Miller, 1956; Milord & Perry, 1977). Add high time pressure to a task can also lead to information overload (Speier, Valacich, & Vessey, 1999). Information overload can be caused by two mechanisms (Speier et al., 1999). The first mechanism is about time pressure. Interruptions consume time that was for completing the primary task. As time pressure intensifies, the likelihood of information overload for the user also increases. If the user sequentially addresses the distraction tasks, time pressure will also increase when they spend time to refocus on the primary task. The second mechanism relates to the growing cognitive demand when the user handles the interruptions. Individuals spend Efforts on distractive information. This can lead to more complex cognitive processing and, in turn, result in information overload.

A lot of studies have found the negative influences of interruption on primary tasks. However, not all the influence of interruption is negative, studies also find that the interruption can have positive influence working performance. While interruptions might cause delays in the current task, they offer an opportunity to address pressing issues that could otherwise become overwhelming later (Hudson et al., n.d.) Interruptions themselves may contain valuable information that can aid primary tasks or activities. Especially when working as a team, team members collaborating in activities with shared goals, resources, deadlines, to-do items, social roles, and work practices can benefit from interruptions that provide updates and changes, as these interruptions help them respond to the changes and effectively integrate them into their work(Carroll et al., 2003). Interruption also acts as a short break from the primary tasks. Those small breaks during work are also considered as a positive practice to enhance focus and foster creativity(Abdullah et al., 2016). A qualitative study of motivation and usage of smartphone found that the use of smartphone frequently interrupted the primary task of the user (Chang et al., 2023). However, the users perceived the smartphone as a tool for improving task performance and promoting their personal well-being rather than only a distraction to primary task (Chang et al., 2023). Additionally, interruptions have the potential to offer valuable information that can aid users in accomplishing their main tasks more effectively (Addas & Pinsonneault, 2015). For example, system-generated alerts may prove to be beneficial for users, even such alerts can be considered interruptions, as security messages frequently obstruct users from completing their primary tasks (Jenkins et al., 2016). Also, according to the study conducted by Addas and Pinsonneault (2018), congruent interruptions are linked to increased subjective workload and are positively correlated with performance effectiveness, leading to better decision-making performance, higher perceived performance, and improved learning.

Some other studies find that the influence of interruption is context dependent. Distraction confluence theory proposes that the conflict in attention between primary and secondary tasks can be induced by unexpected events. This attentional conflict heightens arousal, thereby enhancing performance on simple tasks. However, it also results in cognitive load, impairing performance on complex tasks (Addas & Pinsonneault, 2018; R. S. Baron, 1986; Speier et al., 1999). Several studies in the healthcare industry find that interruptions may have both positive and adverse effects on performance such as nurses' perceived efficiency and job satisfaction (Forsberg et al., 2015). The evidence that the interruption is associated with medical errors is still weak (Grundgeiger & Sanderson, 2009), frequent work interruption is associated with increased workload in doctors, while the interruption may provide valuable information for the primary tasks, such as a warring for error (Weigl et al., 2012). In another study, data shows that when the email interruptions are related to the main task at hand, they exhibit a positive influence on performance. However, when the email interruptions are unrelated to the primary task, they lead to a negative impact on performance(Gefen & Riedl, 2018).

RESEARCH QUESTIONS

Research shows that interruption increase the task completion time (Carayon et al., 2007) Notifications have been widely regarded as interruption, particularly when they come during a primary activity. The harmful effects of interruption can last long after the interruption has ceased. The main goal of this study is to quantify the influence of interruption on the main task.

We want to know how much time could be wasted because of a simple error message in a computer program.

Research questions: How do task-irrelevant computer-based interruptions affect task performance as measured by eye-tracking technology?

METHODOLOGY

Experimental Design

To investigate the influence of computer-based interruption on task performance, a traditional between-subjects experimental design was utilized. Each participant was assigned to one of two groups: the control group or treatment group. In the experiment, participants completed data analysis questions in the "Milo" system, which recorded their eye movement, and performance; after which they answered a brief survey about anxiety and cognitive load.

Experimental Procedure

All participants were undergraduate students and were recruited from a large research university in the United States of America. The students who participated in this experiment were rewarded with extra credit in a class. Students were also provided with alternate extra credit opportunities. In this experiment, a total number of 86 students were recruited. To prevent interaction effects due to selection bias, the participants were randomly assigned to either the control or treatment group. 43 students were assigned to each group. However, the system failed to track the eye movements of 10 students. Therefore, the final sample comprised of 36 students in the control group and 40 students in the treatment group.

In the experiment, participants were asked to answer a series of data analysis questions and a brief survey using the Milo system in a lab setting. The data analysis tasks were presented on a computer and involved the participants selecting the answers to questions based on the information presented in a set of graphs. After answering all the data analysis questions, the participants completed a survey, which was used to capture their anxiety level and cognitive load. Performance was measured by the total time they spent on answering those questions and the accuracy rate of their answers. The survey was designed using Qualtrics and presented in the Milo system. The participants completed the experiment individually in the lab to minimize the unexpected effect of other distractions or social influences.

The lab used for the experiment was a 5 * 5-meter space. Participants sat in front of a desktop computer and were monitored with an attached camera. In the lab, three stations were available. However, to prevent the participants from influencing each other, only the middle station was utilized to collect data.

Prior to starting the experiment, all participants read and signed the informed consent form. Furthermore, the participants received verbal instructions about the Milo system and the corresponding analysis questions. The verbal instructions were consistent across both groups. While performing the data analysis task, all participants answered each question based on a data graph (see Figure 1). Participants were able to view each question only once. Each participant was allowed up to 15 minutes to finish the entire process.

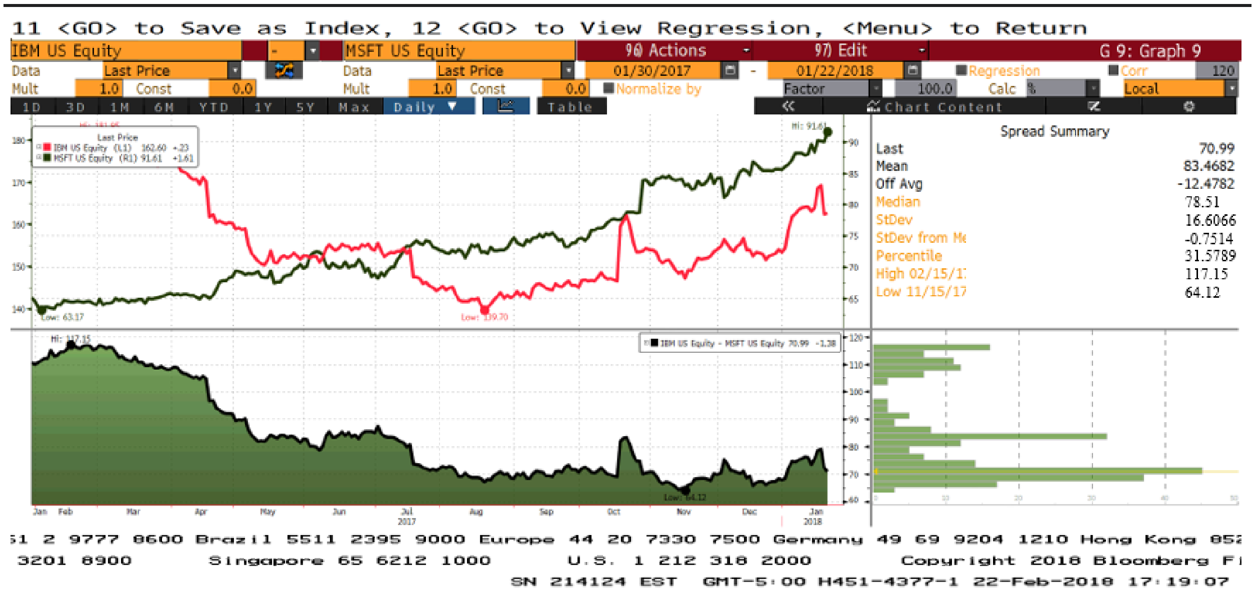

Figure 1. Data graph example

Experimental Manipulation

A designed interruption was used as the manipulation in the treatment group. In this group, the distraction acted as an external stimulus, and participants passively responded to the stimulus before continuing their task. The distraction was a pop-up message (see Figure 2). After the participant worked on the question for 10 seconds, the distraction page automatically popped-up and blocked the question screen. The participants were required to follow the instructions on the distraction page, which asked them to click the Shift + Space key to get rid of the pop-up window and continue their task. The iMotions facial recording was used to record how the participants handle this interruption. No manipulations were used on the control group in the experiment.

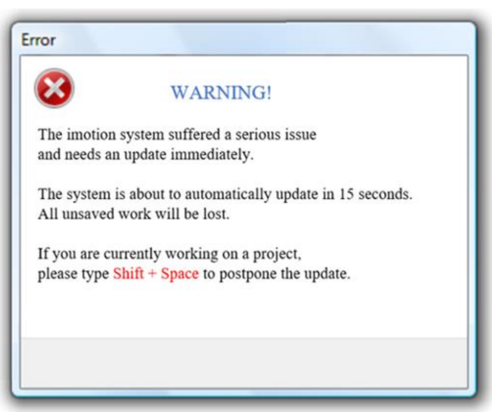

Figure 2. Pop-up message

Tools for Measurement

During the experiment, participants answered data analytics-type questions using a system named Milo, which is an eye movement and facial expression-capture system. It uses eye tracking hardware (Tobii X60) and iMotions software (version#) to assess visual attention measured by gaze and fixation characteristics.

Measurement

To investigate the influence of distraction on users' behaviors, the following theories were used as the underlining theoretical foundation for this research: memory for goal theory, processing efficiency theory, attentional control theory, cognitive load theory, working memory theory, distraction conflict theory, and resource matching theory. Four constructs were used in this research: distraction, anxiety, cognitive load, and task performance. Two constructs, anxiety and cognitive load, are physiological measures. The other two constructs, distraction and task performance, are direct measures of behavior.

The study aims to compare the users' performance across the control group (0) and distraction group (1). Performance was directly measured as participants' time spent on the data analysis questions immediately after the distractions.

Performance

Less time spent on a task indicates better performance. The iMotions system records the time each user takes to complete a question; in this study, that time was recorded to the millisecond, although for analysis, the time was converted into seconds to ensure the results interpretation had more practical implementation.

Time is measured in seconds and only includes the time participants spent answering the analysis questions. The task time begins after participants first fixate on the questions. It does not include the time participants spent on distractions. The task time also does not include the time spent on responding to the distraction message. The camera recordings of facial expressions also indicate when and whether the participant pays attention to working on the secondary task.

Considerations of the Design

One consideration of the design is the learning effect. The tasks are graphical analysis questions. The participants were asked to read the graphs and answer questions based on the information on the graph. Because participants have different levels of ability to solve this type of question, the first 12 questions, which are presented before the distraction, help participants learn how to solve these questions and include all the possible types of questions and graphs used in this study. After solving the first 12 questions, participants should be able to solve all the questions after the distraction.

The manipulation in this research is the participants' attention. If the participant reads the distractive material and shifts their attention away from the primary task, it means that the manipulation works. The iMotions systems recorded the participants' behaviors, which can be used to support manipulation check.

DATA ANALYSIS & RESULTS

SPSS version 28.0.1.1 (IBM Corp., 2012) was used for hypothesis testing and preliminary and post-hoc data analyses. Several one-way analyses of variance (ANOVAs) were conducted to test the influence of distractions on user performance. Fixation and gazed point are also additionally measured using the metrics recorded by the iMotions.

ANOVA was carried out to test the hypothesis that there is a significant difference in participants' task completion time followed by interruption. The results of a one-way ANOVA showed there was a significant effect of interruption on time spent on task ($F [1, 84] = 13.74$, $p <.001$). Participants in the control condition ($n = 43$, $M = 38.802$, $SD = 17.986$) spent less time on the primary task than participants in the treatment group ($n = 43$, $M = 53.516$, $SD = 18.819$). Furthermore, the assumption of homogeneity of variances was tested and satisfied based on Levene's F test ($F [1,84] = .03$, $p = .863$). The data supported our hypothesis.

We use dummy code for accuracy of the task, "1" means correct and "0" means incorrect. The results of a one-way ANOVA showed that there is no statistically significant difference in the effect of distraction on the accuracy with which participants performed the task ($F [1, 84] = .058$, $p = .810$). Participants in the control condition ($n = 43$, $M = .72$, $SD = .45$) showed a similar accuracy rate for the primary task as those in the interruption condition ($n = 43$, $M = .72$, $SD = .40$).

Saccades are quick, simultaneous movements of both eyes between two or more phases of fixation. In this experiment, the saccade rate refers to the frequency of rapid eye movements made by a person during a task. iMotions record also shows that distracted individuals would have a higher saccade rate and a lower fixation rate than undistracted individuals. The fixation rate was collected by iMotions, with a data set of 76 eye tracking measurements successfully collected. The results of a one-way ANOVA showed that there was no statistically significant effect of distraction on saccade rate ($F [1, 74] = .48$, $p = .49$). Participants in the control condition ($n = 36$, $M = 37.22$, $SD = 15.05$) had a lower saccade rate than those in the interruption condition ($n = 40$, $M = 39.62$, $SD = 15.21$).

iMotion record shows that the distraction group would spend more time on fixation. The results of a one-way ANOVA showed that there was a significant effect of distraction on fixation time spent on task ($F [1, 74] = 4.013$, $p = .01$). Participants in the undistracted group ($n = 36$, $M = 24.14$, $SD = 11.58$) spent less time on fixation than those in the interruption condition ($n = 40$, $M = 31.86$, $SD = 13.56$). Furthermore, the assumption of homogeneity of variances was tested and satisfied based on Levene's F test ($F [1,74] = .214$, $p = .65$). Appendix A shows the output pages from SPSS.

DISCUSSION OF THE RESULT

The hypothesis tests the relationship between interruption and task completion time. The result of our study supports our hypothesis in the experiment. We proposed that Individuals who are interrupted by computer-based interruption will take longer time to complete a task than those who are not distracted. More specifically, it was predicted that after being interrupted by a computer-based interruption, the users' efficiency in completing a task is temporarily reduced. The data indeed shows that distracted individuals spent more time on the primary task, although the accuracy of their answers was similar to that of the undistracted individuals. According to process efficiency theory, individuals can adjust the time spent on a task and its effectiveness while keeping efficiency constant(Eysenck & Calvo, 1992). When distracted, an individual's efficiency is lower, forcing participants to decide whether to spend more time or accept reduced output quality. In this study, individuals chose to invest more time to maintain accuracy. On average, to complete the same questions as undistracted individuals with similar accuracy, participants spent an additional 14.71 seconds in the computer-based interruption condition. These findings support our hypothesis.

The findings show an increase in saccade rate after distraction. One of the explanations proposed by previous research is that the saccade rate consistently reflects individuals' anxiety level (Tichon, Wallis, Riek, & Mavin, 2014). Attentional control theory suggests that distraction increases anxiety because it influences the function of the attentional control system (Eysenck & Derakshan, 2011). This study utilized eye movement data to confirm the increase in saccade rate following distraction. Undistracted individuals had lower saccade rates than computer-based interrupted participants. This finding supports that participants may experience higher levels of anxiety.

The findings show an increase in Fixation time after distraction. Research has found that an increase in fixation is associated with cognitive load increase (Gould, 1973). Cognitive load theory posits three types of cognitive load: intrinsic, extraneous, and germane (Paas et al., 2003). Distraction increases both intrinsic and extraneous loads, placing greater demands on working memory resources. The data reveal that distracted participants spent more time fixating on the area of interest, which previous research has shown to be an indicator of cognitive load (Behroozi et al., 2018; Marandi, Madeleine, Omland, Vuillerme, & Samani, 2018). These findings support the idea that distraction indeed increases cognitive load.

Implications for research

This research contributes significantly to the field of information systems (IS) scholarship in several ways. Firstly, it delves into the impact of distractions on individual task performance by combining distraction-conflict theory (R. S. Baron, 1986) and cognitive load theory(Paas et al., 2003). These two theoretical frameworks were integrated to provide a comprehensive explanation of how interruptions caused by computer systems affect the completion of primary tasks.

Secondly, this study takes a unique approach by utilizing a physiological tool, as opposed to relying solely on perception, to measure cognition and task performance. This approach was recently designed in IS research areas, and the present work addresses this gap by employing an eye tracking system developed by iMotions. This system serves as a subjective measurement tool, capturing various aspects of an individual's behavior during task execution, such as the time spent on a task and the cognitive load experienced.

Third, the study explores the impact of singular interruptions on task performance. Even though there are numerous research studies on distraction in terms of frequency and timing, there is a notable scarcity of studies addressing one-time interruptions specifically caused by computer systems. The present study bridges this gap by concentrating on this specific form of interruption and its consequences. One of the challenges when investigating momentary distractions is the need for highly accurate measurements to detect subtle effects. In this study, where the performance differences among individuals are only a matter of seconds, the eye tracking system proves to be ideal to precisely recording individual behaviors. In this research, the iMotions system employed is capable of measuring task execution times down to the millisecond.

Implications for practice

This research also offers valuable practical insights. It provides empirical evidence that computer interruptions not only prolong task completion time due to the additional time spent on resolving the issue but also increase the effort required to complete the primary task following the interruption event. The study reveals that an individual's performance experiences a decline even with a brief, one-time interruption.

From a managerial standpoint, these findings underscore the importance of companies accurately assessing the repercussions of system issues, considering the lingering effects even after the system problem has been resolved. The extended duration of distraction arises not solely from the time allocated to addressing a secondary task but also from the impact of such tasks on the cognitive processes of employees.

Finally, this study revealed that distractions lead to elevated levels of both anxiety and cognitive load. Anxiety, being a negative emotion, can significantly undermine employee productivity. Consequently, the management of emotions becomes a crucial element of an organization's comprehensive management strategy, particularly in situations where employees are extensively involved in multitasking. In response to these findings, a manager can implement strategies to reduce interruptions and hence regulate employees' emotional responses, thereby mitigating the adverse consequences of distractions on their performance.

CONCLUSION

This research has significantly enhanced our understanding of how distractions impact task performance. To address the research question: How do task-irrelevant computer-based interruptions affect task performance as measured by eye-tracking technology? This study utilizes eye tracking systems to monitor individuals' behavior across undistracted, mandatory interruption, and multitasking conditions, subsequently comparing their behaviors.

The data gathered clearly demonstrates that task-irrelevant distractions have a detrimental effect on users, leading to increased levels of anxiety and cognitive load while simultaneously reducing the overall efficiency in completing primary tasks. Notably, the study reveals that both the time allocated to primary tasks and secondary responsibilities is extended when secondary tasks disrupt the execution of primary tasks.

Furthermore, this research effectively implemented eye tracking as a data collection and analysis method, highlighting its promise as a valuable approach for gathering behavioral data in distraction-related research.

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