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Adoption of IT Governance Strategies for Multiproduct DevOps Teams: A Correlational Quantitative Study

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

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Abstract

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MS, University of Liverpool, 2013

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Abstract

Many multiproduct delivery organizations have difficulty adopting Information Technology (IT) governance practices within their Development and Operations (DevOps) teams. IT leaders who are managing DevOps teams, need to understand the factors influencing IT governance (ITG) adoption; otherwise this may impact DevOps maturity, resulting in reduced product delivery capabilities. Grounded in the technology acceptance model, the purpose of this quantitative correlational study was to examine the relationship between performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), as moderated by experience (EXP), gender (GND), age (AGE), and voluntariness of use (VOL) with behavioral intention (BI) to adopt and use (USE) IT governance (ITG), within their organizations. The participants ($n=205$) were IT leaders in various global professional LinkedIn groups, who specialized in DevOps and ITG-related frameworks. The results of the partial least squares analysis indicated that PE ($p1$=.234) and SI ($p3$=.655) have a positive correlation with the DevOps leaders' BI to adopt ITG (R^2=.692). FC ($p4$=.753) positively correlates with the adoption and USE of ITG (R^2=.677). IT leaders who intend to use ITG practices (BI) in order to enhance DevOps capabilities need to engage relevant stakeholders (SI) through specific KPIs related to product delivery (PE) whilst leveraging ITG and DevOps expertise. Furthermore, ITG adoption is facilitated (FC) when implemented early in the DevOps transformation. The implications for positive social change include the potential to improve organizational culture and increase product quality through a sustainable IT environment.

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Dedication

I would like to dedicate this work to my wife Maria Graziella for her continuous support. Thank you for encouraging me to continually improve and aspire for greater things.

Acknowledgments

I want to thank my committee, Dr Phillips, and Dr. Tsehay for guiding me throughout this Doctoral study. Special acknowledgment to Dr. Taylor (Walden) and Dr. Camilleri (University of Malta) for their assistance in the statistical analysis. Also, I would like to acknowledge all the Walden faculty and student support team for an excellent educational experience.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Software-delivery organizations are shifting their operating models to become agile, thus increasing productivity, reducing time to market, and becoming faster in reacting to changes (Beecham et al., 2021). As part of this transformation, organizations shift software projects into products in conjunction with establishing a DevOps function, to achieve continuous integration and delivery. However, managing DevOps teams in highly agile environments involving several products, presents various challenges in terms of alignment related to skills, technology, architecture, and teams' structure. Through the adoption of principles found in Control Objectives for Information and Related Technologies (COBIT-5), Information Technology Infrastructure Library (ITIL) and The Open Group Architecture Framework (TOGAF) frameworks, organizations rely on ITG to effectively address these challenges. In this study, I focused on understanding what motivates IT leaders to adopt such ITG strategies for multiproduct DevOps teams.

In this section of the study, I discussed the background of the problem, problem statement, purpose statement, nature of the study, research question and the conceptual framework of the study. I also discuss the definitions of terms, assumptions, limitations, delimitations, and significance of the study. In the review of academic and professional literature section, I include research and professional work focused on the adoption of ITG strategies for multiproduct DevOps teams.

Background of the Problem

Organizations that adopt ITG amongst DevOps teams are able to build reliable products that adhere to compliance, traceability, trust, and quality. IT leaders use ITG to achieve applicable uniformity amongst the cooperating DevOps teams by inspiring innovation whilst ensuring compliance with standards and guidelines (Bass & Haxby, 2019). Performance, compliance, and effort are key elements IT leaders consider when adopting ITG strategies amongst DevOps teams within software delivery organizations (Alghamdi et al., 2020). IT leaders who fail to understand the usefulness of adopting ITG strategies in DevOps teams, negatively affect the competitive advantage multiproduct delivery organizations aim for, through reliability, performance, agility and minimizing costs (Levstek et al., 2018). The existing literature does not include a comprehensive analysis of critical factors, challenges, and measurable indicators for the adoption of ITG in multiproduct DevOps teams.

My goal for this study was to fill this specific research gap by identifying such critical factors and measurements. An approach including perceived usefulness, perceived ease of use and BI to use ITG practices, may provide IT leaders with effective strategies to the actual implementation and usage of ITG throughout DevOps teams (Davis, 1989). Future work should focus on the inclusion of other teams within the software delivery process such as security and data teams.

Problem Statement

As organizations are adopting DevOps practices within their environments, 40% of new products are estimated to fail at launch (Cooper, 2019). The failure rate of products increases with the product size, whereby only 5% of large products are considered successful based on end user value, cost, time, productivity, and technical quality (Jorgensen, 2019). The general IT problem is the lack of ITG amongst DevOps teams within multiproduct delivery organizations. The specific IT problem is that some IT leaders in multiproduct delivery organizations, are not aligned with the relationship between PE, EE, SI, and FC, as moderated by EXP, AGE, GND, VOL, with BI to adopt ITG amongst DevOps teams.

Purpose Statement

The purpose of this quantitative correlational study was to identify the relationship between IT leader's PE, EE, SI, and FC with BI to adopt and USE ITG amongst DevOps teams within multiproduct delivery organizations. The dependent variable was the IT leaders' adoption of ITG, while the independent variables were IT leaders' perceptions of PE, EE, SI, FC, BI, and USE. I used the UTAUT model as the theoretical framework for this study. I conducted data collection through a validated UTAUT survey instrument and performed a partial least square analysis. The population for this study included IT leaders within my personal LinkedIn connections and groups, such as chief technology officers (CTOs), chief information officers (CIOs), IT head of departments, IT managers and team leaders within architecture, development, and operations teams, operating in multiproduct delivery organizations. The population of the study did not have a specific geographic location and was scattered globally. This study may impact social change by improving software delivery thereby positively affecting uptime, reliability, and functionality so important for the consumers and society.

Nature of the Study

For this study, I used a quantitative partial least square analysis to identify the critical factors and their underlying relationships leading to the intent to implement an ITG strategy for DevOps teams within multiproduct delivery organizations. I used a quantitative study to identify the relationship between critical factors contributing to ITG adoption for DevOps teams. Farahani et al. (2010) found that PLS regression resulted in more stable results compared to ordinary least square regression (OLS) when the sample size is small. Furthermore, Cramer et al. (1988) indicated that bootstrapping and cross-validation found in PLS result in an improved chance correlation as opposed to multiple regression.

A quasi-experimental design involves the assignment of both experimental and control groups without random assignment (Miller et al., 2020). A quasi-experimental design was not suitable for this study because of the availability of subjects to use in the experimentation period and due to the length of the study. A case study approach requires the researcher to adopt a thematic analysis technique to understand how such factors contribute to ITG adoption amongst software delivery organizations. Furthermore, a qualitative approach requires the researcher to use methodological triangulation involving different data sources such as interviews and observations (see Fusch et al., 2018). I did not use qualitative research because it includes phenomenological, ethnographic, or case study designs (Jamali, 2018), based on descriptive data, to study a social phenomenon occurring in real life, which does not apply to my research question.

In quantitative research designs, researchers use statistical techniques to quantify a problem through numerical data and test hypotheses (Bloomfield & Fisher, 2019). A quantitative study can be conducted to explain how such factors contribute towards ITG, using a validated survey with qualified subjects.

In this study, I used a partial least square analysis to identify relationship of various independent variables (PE, EE, SI, FC) and the dependent variable behavioural intent (BI) to adopt ITG. I used this type of analysis to identify causal explanations by examining both the cause and effect. Covariance is used to determine the quantitative gradations on dimensions (Krause, 2018). I used this research design to determine if a significant relationship amongst critical factors contributing to ITG amongst software architecture, development and DevOps teams exists.

Research Question and Hypotheses

Research Question (RQ): What is the relationship between PE, EE, SI, and FC, as moderated by GND, AGE, EXP, and VOL with BI to adopt ITG for multiproduct DevOps teams?

Null Hypothesis 1 ($H_0 1$): PE is not related to the BI to adopt ITG.

Alternative Hypothesis 1 ($H_a 1$): PE is positively related to the BI to adopt ITG.

Null Hypothesis 2 ($H_0 2$): EE is not related to the BI to adopt ITG.

Alternative Hypothesis 2 ($H_a 2$): EE is positively related to the BI to adopt ITG.

Null Hypothesis 3 ($H_0 3$): SI is not related to the BI to adopt ITG.

Alternative Hypothesis 3 ($H_a 3$): SI is positively related to the BI to adopt ITG.

Null Hypothesis 4 ($H_0 4$): FC are not related to the use of ITG.

Alternative Hypothesis 4 ($H_a 4$): FC are positively related to the use of ITG.

Null Hypothesis 5 ($H_0 5$): BIs are not related to the adoption of ITG.

Alternative Hypothesis 5 ($H_a 5$): BIs are positively related to the adoption of ITG.

Null Hypothesis 6 ($H_0 6$): EXP has no moderating effect on the relationship between EE and BI to adopt ITG.

Alternative Hypothesis 6 ($H_a 6$): EXP has a moderating effect on the relationship between EE and BI to adopt ITG.

Null Hypothesis 7 ($H_0 7$): EXP has no moderating effect on the relationship between SI and BI to adopt ITG.

Alternative Hypothesis 7 ($H_a 7$): EXP has a moderating effect on the relationship between SI and BI to adopt ITG.

Null Hypothesis 8 ($H_0 8$): EXP has no moderating effect on the relationship between FC and use of ITG.

Alternative Hypothesis 8 ($H_a 8$): EXP has a moderating effect on the relationship between FC and use of ITG.

Null Hypothesis 9 ($H_0$9): GND has no moderating effect on the relationship between PE and BI to adopt ITG.

Alternative Hypothesis 9 (H_a9): GND has a moderating effect on the relationship between PE and BI to adopt ITG.

Null Hypothesis 10 ($H_0$10): GND has no moderating effect on the relationship between EE and BI to adopt ITG.

Alternative Hypothesis 10 (H_a10): GND has a moderating effect on the relationship between EE and BI to adopt ITG.

Null Hypothesis 11 ($H_0$11): GND has no moderating effect on the relationship between SI and BI to adopt ITG.

Alternative Hypothesis 11 (H_a11): GND has a moderating effect on the relationship between SI and BI to adopt ITG.

Null Hypothesis 12 ($H_0$12): AGE has no moderating effect on the relationship between PE and BI to adopt ITG.

Alternative Hypothesis 12 (H_a12): AGE has a moderating effect on the relationship between PE and BI to adopt ITG.

Null Hypothesis 13 ($H_0$13): AGE has no moderating effect on the relationship between EE and BI to adopt ITG.

Alternative Hypothesis 13 (H_a13): AGE has a moderating effect on the relationship between EE and BI to adopt ITG.

Null Hypothesis 14 ($H_0$14): AGE has no moderating effect on the relationship between FC and use of ITG.

Alternative Hypothesis 14 (H_a14): AGE has a moderating effect on the relationship between FC and use of ITG.

Null Hypothesis 15 ($H_0$15): AGE has no moderating effect on the relationship between SI and BI to adopt ITG.

Alternative Hypothesis 15 (H_a15): AGE has a moderating effect on the relationship between SI and BI to adopt ITG.

Null Hypothesis 16 ($H_0$16): VOL has no moderating effect on the relationship between SI and BI to adopt ITG.

Alternative Hypothesis 16 (H_a16): VOL has a moderating effect on the relationship between SI and BI to adopt ITG.

Survey Questions

1. Are you an IT leader over the age of 18, for an organization delivering multiple products in a DevOps environment?
2. Does your organization utilize ITG to manage DevOps teams?
3. Are you part of the ITG body within your organization?
4. Is it mandatory for your organization to have an ITG body?
5. Did your organization instruct you to adopt an ITG strategy?
6. What type of ITG method is used in your organization?

7. What is your age bracket?
    a. Under 30
    b. 31–40
    c. 41–50
    d. Over 51
8. What is your level of experience working with multiproduct DevOps environments?
    a. Under 1 year
    b. 1–2 years
    c. 3–4 years
    d. More than 5 years
9. Do you have any certifications related to ITG, Enterprise Architecture, Service Management, or Software Architecture (COBIT, TOGAF, ITIL, COBIT, etc.)?
10. What is your gender?
    a. Male
    b. Female
11. It is mandatory for my organization to have an ITG body.
    a. Yes
    b. No
12. My organization instructed me to adopt/participate in an ITG body.

a. Yes

b. No

13. I agree with the ITG method adopted/used in my organization.

a. Strongly Disagree

b. Disagree

c. Neither Agree nor Disagree

d. Agree Strongly

e. Agree

14. What is the size of the company?

a. Less than 100 employees

b. 101-250 employees

c. 251-500 employees

d. 501-1000 employees

e. Over 1001 employees

15. What is the annual revenue of the company?

a. Less than $1 million

b. $1 million - $5 million

c. $5 million - $10 million

d. $10 million - $20 million

e. Over $20 million

16. What type of ITG is used in your organization?

a. COBIT
b. ITIL
c. Enterprise Architecture (TOGAF/ZACHMAN)
d. ISO27001
e. Other

17. Performance expectancy of ITG

a. I find the adoption/use of ITG strategies useful to manage DevOps teams.
b. Adopting/Using ITG strategies enable DevOps teams to accomplish tasks more quickly.
c. Adopting/Using ITG strategies increases the productivity of DevOps teams.
d. Adopting/Using ITG strategies increases the alignment of DevOps teams with other IT teams.
e. Adopting/Using ITG strategies increases the alignment of DevOps teams with other business departments.
f. Adopting/Using ITG strategies allow DevOps teams to improve the delivery of the end products.

18. Effort expectancy of ITG

a. My role in the adoption/participation of an ITG framework is clear and understandable.

b. My interaction with other stakeholders in the adoption and participation of ITG is clear and understandable.

c. I currently find it easy to adopt and participate in an ITG framework.

d. Learning to adopt and participate in an ITG framework is easy.

19. Social influence of ITG

a. People in my organization, who influence my behavior, think that I should adopt/participate in an ITG framework.

b. DevOps engineers think that I should adopt/participate in an ITG framework.

c. The senior management of my organization was helpful in adopting ITG.

d. In general, the organization supports the adoption and value of ITG.

20. Facilitating conditions of ITG

a. I have the necessary resources to adopt/collaborate in an ITG framework.

b. I have the necessary knowledge to adopt/collaborate in an ITG framework.

c. Specialized training is available to assist me in adopting/collaborating in an ITG framework.

d. A specific person (or group) is available for assistance when I face difficulties in the adoption/participation in an ITG framework.

21. Behavioral intention to adopt ITG to manage multiproduct DevOps teams
    a. I intend to adopt/participate in an ITG framework in the next 12 months.
    b. I predict I would adopt/participate in an ITG framework in the next 12 months.
    c. I plan to adopt/participate in an ITG framework in the next 12 months.
22. Adoption of ITG to manage multiproduct DevOps teams
    a. Participating in an ITG framework is a core responsibility of my role in my organization.
    b. I spend a lot of time modifying the structure of the ITG framework currently used in my organization.
    c. I participated in different ITG frameworks within my organization.
    d. I consistently participate in an ITG framework.

Theoretical Framework

The theory upon which this study was grounded, to study the acceptance and use of ITG for DevOps teams within multiproduct delivery organizations is UTAUT. The UTAUT model was developed by Venkatesh et al. in 2003 to predict technology acceptance in organizational settings. The constructs of UTAUT derive from 8 different theories and models comprising of theory of reasoned action (TRA), technology acceptance model (TAM), motivational model (MM), theory of planned behavior (TPB), combined TAM and TPB (C-TAM-TPB), model of PC utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT). Venkatesh et al. (2003) developed the UTAUT model whereby the adoption of ITG is dependent on constructs PE, EE, SI, FC, BI, and moderated by AGE, GND, EXP and VOL. Table 1 explains the origins and rational of each UTAUT construct. Existing literature acknowledges PE as the key driver towards adoption of DevOps and ITG. However, Caluwe and De Haes (2019) identified a gap in literature related to the relation of board-level ITG and effect on firm performance in terms of internal value and competitive value. My study might provide insight in this area.

Table 1

UTAUT Constructs and Origins

Constructs	Definition	Variables	Model Contributing to Constructs
PE	The degree to which an individual believes that using the system will help him or her to attain gains in a job.	Perceived Usefulness	TAM 1-3 and C-TAM-TPB
		Extrinsic Motivation	MM
		Job-fit	MPCU
		Relative Advantage	IDT
		Outcome expectations	SCT
EE	The degree of ease associated with the use of the system	Perceived Ease of Use	TAM 1-3
SI	The degree to which an individual feels that it is important for others to believe he or she should use the system.	Subjective Norms	TRA, TAM2, TPB and C-TAM-TPB
		Social Factors	MCPU
		Image	IDT
FC	The degree to which an individual believes that organizational and technical infrastructure exists to support the use of the system.	Perceived Behavioral Control	TPB and C-TAM-TPB
		FC	MPCU
		Compatibility	IDT

Note. Adapted/Reprinted from "UTAUT and UTAUT 2- A review and Agenda for future research" by A. Chang, 2012, *The Winners*, 13(2), p. 109-110.

Table 2

Constructs and Corresponding Items

Construct	Corresponding Items	Items Source
PE	*PE1*: I find the adoption and use of ITG strategies useful to manage DevOps teams. *PE2*: Adopting and using ITG strategies enable DevOps teams to accomplish tasks more quickly. *PE3*: Adopting and using ITG strategies increase the productivity of DevOps teams. *PE4*: Adopting and using ITG strategies increase the alignment of DevOps teams with other IT teams. *PE5*: Adopting and using ITG strategies increase the alignment of DevOps teams with other business departments. *PE6*: Adopting and using ITG strategies allow DevOps teams to improve the delivery of the end products.	Adopted from Venkatesh et al. (2003); Bervell & Umar (2017)
EE	*EE1*: My role in the adoption and participation of an ITG framework is clear and understandable. *EE2*: My interaction with other stakeholders in the adoption and participation of ITG is clear and understandable. *EE3*: I currently find it easy to adopt and participate in an ITG framework. *EE4*: Learning to adopt and participate in an ITG framework is easy.	Adopted from Venkatesh et al. (2003)
SI	*SI1*: People in my organization, who influence my behavior, think that I should adopt and participate in an ITG framework. *SI2*: DevOps engineers think that I should adopt and participate in an ITG framework. *SI3*: The senior management of my organization was helpful in adopting an ITG framework. *SI4*: In general, the organization supports the adoption and value of ITG.	Adopted from Venkatesh et al. (2003)
FC	*FC1*: I have the necessary resources to adopt and collaborate in an ITG framework. *FC2*: I have the necessary knowledge to adopt and collaborate in an ITG framework. *FC3*: Specialized training is available to assist me in adopting and collaborating in an ITG framework. *FC4*: A specific person (or group) is available for assistance when I face difficulties in the adoption and participation of an ITG framework.	Adopted from Venkatesh et al. (2003)
BI	*BI1*: I intend to adopt and participate in an ITG framework in the next 12 months. *BI2*: I predict I would adopt and participate in an ITG framework in the next 12 months. *BI3*: I plan to adopt and participate in an ITG framework in the next 12 months.	Adopted from Venkatesh et al. (2003)
Use	*USE1*: Participating in an ITG framework is a core responsibility of my role in my organization *USE2*: I spend a lot of time modifying the structure of the ITG framework currently used in my organization. *USE3*: I participated in different ITG frameworks within my organization. *USE4*: I consistently participate in an ITG framework.	Adopted from Venkatesh et al. (2003); Bervell & Umar (2017)

In this quantitative survey and analysis based on UTAUT theory, I demonstrated the correlation towards the adoption of ITG for multiproduct DevOps teams, through different constructs (PE, EE, SI, and FC) and moderated by EXP that determined BI and use behavior. The UTAUT theory was successfully implemented by other researchers to address IT related problems, whereby Anderson (2019) quantitatively measured factors affecting continuous delivery. Other frameworks that were used in this study derive from industry standards, specifically COBIT, ITIL, TOGAF and ZACHMAN frameworks. These were used in the discussion after the quantitative study was completed.

Definition of Terms

This section provides clarity between the reader and the author by defining key terms and concepts used in this study.

Agile software development, refers to a group of software development methodologies leveraging collaborative engagement amongst different team members and fast release of artifacts, within a fast-paced environment through iterative cycles of development (Zaitsev et al., 2020).

Control Objectives for Information and Related Technologies (COBIT), is an enterprise-wide ITG framework guiding organizations in assessing, leading, and monitoring IT usage, necessitating a culture encompassing organizational structures and processes that align to the corporate vision (Amorim et al., 2020).

DevOps, is a concept aimed to build a close collaboration amongst development and operations activities, thus leveraging the benefits of agile software development (Lwakatare et al., 2019). Key components in a DevOps environment are Continuous Integration, Continuous Deployment and Continuous Delivery (CI/CD/CD). Continuous

Integration refers to the automation of software build jobs components including compiling and testing, whereas Continuous Deployment and Continuous Delivery refer to the automation of software deployment across the various environments (Debroy & Miller, 2020; Laukkanen et al., 2018), ensuring quality assurance is guaranteed in production.

Enterprise Architecture (EA), is a method to define the inner components of an organization from various point of views in order to align the organizational strategy, resources and processes thus becoming more efficient (Menglong et al., 2020). Two prominent enterprise architecture frameworks are TOGAF and ZACHMAN.

IT Governance (ITG), is a practice adopted by organization to enhance and extend business operations by simplifying the consumption of IT within the enterprise (Najjar et al., 2020).

Information Technology Infrastructure Library (ITIL), is a popular IT Service Management (ITSM) framework utilizing customer centricity to optimize and improve IT services (Obwegeser et al., 2019).

Product, is the term given to an AGILE-driven software initiative or project, whereby a multi-faceted team is allocated to the software throughout its lifecycle (Bass & Haxby, 2019). A multiproduct organization is therefore an entity that builds and continuously delivers multiple products. Such products can either be part of a holistic ecosystem or separate non-related products.

Assumptions, Limitations, and Delimitations

Assumptions

This study contains different types of philosophical assumptions related to human knowledge (epistemological), existing researcher's knowledge on the problem (ontological), and researcher's influence on the study (axiological). These philosophical assumptions occur naturally in research (Almasri & McDonald, 2021). The researcher assumed that the quantitative methodology was an effective method to understand the constructs of this study. Another assumption was that a valid gap in the body literature existed with regards to a comprehensive analysis of critical factors, challenges, and measurable indicators for the adoption for the adoption of ITG in multiproduct DevOps teams. Furthermore, the researcher assumed that the UTAUT theoretical framework is an appropriate research design for this study. The researcher assumed that the participants meet the selection criteria for this study, and they have provided honest answers in the quantitative survey.

Furthermore, UTAUT was considered more suitable than UTAUT2, because the additional constructs (hedonic motivation, price, and habit) in the second version are focused on technology rather than processes. Hence such constructs are assumed not to directly impact the BI to adopt ITG. Moreover, the researcher assumed that the participant understood the scope of the study and the questions in the survey. Additionally, the research assumed that the participants answered the survey honestly.

Lastly, the researcher assumed that the sample size of the study provides a true representation of the target population.

Limitations

Limitations are weaknesses that challenge the validity of the study and are usually out of the researcher's control (Theofanidis & Fountouki, 2018). It is necessary to identify the limitations in any literature to give the audience the necessary understanding of the research and hence allow future researchers to build upon this study (Randazzo et al., 2021). This study had limitations related to research design, sample size and timeframe. Lastly, this quantitative study provided correlational information regarding the constructs towards adoption of ITG without explaining the methodologies used for adoption.

Delimitations

Delimitations are limitations intentionally introduced by the researcher to establish boundaries whilst achieving the scope of the study (Theofanidis & Fountouki, 2018). The participants in this study had leadership positions in DevOps teams, operating in multiproduct delivery organizations with an understanding of ITG. These participants were authoritative in the adoption of ITG strategies within their organizations. Lastly, this quantitative study identified the correlation amongst the constructs towards adopting ITG but does not discuss the adoption strategies used by the participants.

Significance of the Study

Contribution to Information Technology Practice

This study is significant in that it provided a clear understanding on the dependencies and relationships amongst the adoption process for ITG, thus improving the overall IT strategy and alignment. This may allow IT leaders to deliver appropriate strategy amongst the various software delivery teams, thus improving service delivery.

Implications for Social Change

ITG provides organizations with the necessary support to implement industry standards and best practices, thus improving their DevOps processes and products (Bollen et al., 2018). Improvement to the product service delivery, positively affects products' uptime, reliability, and functionality. Such gains are important for the public, since product disruptions or lack of functionality, reduce the customer EXP and overall service offering. Specifically, reliability is an essential feature of any software as a service (SaaS) offering, whereby the community consumes such services as a commodity as required. These services include banking, entertainment, education, and communication. Hence it is paramount that such services provide the best reliability in terms of performance, features, and security to ensure the safeguarding and optimum experience for the public.

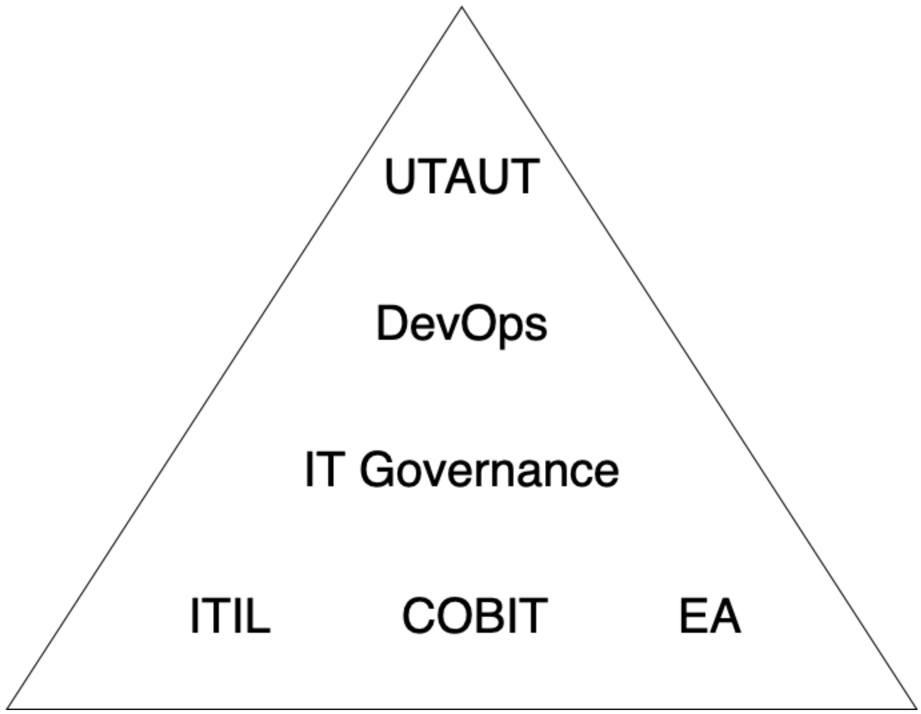
A Review of the Professional and Academic Literature

Opening Narrative

The purpose of the research question in this study was to quantitatively explore the relationship between PE, EE, SI, and FC, as moderated by EXP, AGE, GND, and VOL, with the BI to adopt ITG for DevOps teams, within multiproduct delivery organizations. The exploration of ITG adoption using the UTAUT framework is not adequately documented, primarily because UTAUT was used for technology adoption rather than frameworks. Furthermore, ITG adoption research is predominantly qualitative in nature. Hence, previous researchers focused on strategies and factors based on case studies and frameworks such as COBIT, ITIL or TOGAF. A gap in literature exists pertaining to drivers and internal mechanics that influence IT leaders in the adoption of ITG. In this quantitative study, I explored the UTAUT constructs and moderators to determine the adoption of ITG in DevOps teams. UTAUT constructs and moderators, including PE, EE, SI, FC, EXP, AGE, GND, and VOL were identified and discussed by various researchers using other theoretical or conceptual frameworks. I reviewed these studies and identified pertinent themes. Figure 1 is a high-level overview of the central themes used in the search of literature.

Figure 1

Central Themes of Research



The rapid adoption of ITIL, EA and COBIT amongst DevOps teams can be attributed to isomorphic pressure in the form of coercive, normative, or mimetic (DiMaggio & Powell, 1991). The highest adopted ITIL principles indicate that organizations are focused on operational delivery. Hence, it can be posited that ITIL is used to govern/manage the operational team, whereas agile frameworks are more focused on development teams. EA is a holistic framework used by IT leaders to manage both development and operations teams from an enterprise-wide perspective. The shortcomings posed by EA can be addressed by the structure of COBIT. Additionally, ITIL4 addresses the gaps found in the third version, to effectively manage the service value chains delivered by DevOps teams.

For this study, I used literature mostly located using ACM Digital Library, IEEE Explore Digital Library, ScienceDirect and ProQuest Central. Most of the literature used in this study is dated post 2017, thus ensuring latest research and practices related to the research question. Furthermore, I referred to seminal work regarding adoption theories and governance. The search strings, criteria and databases used for this review are shown in Table 3, hereunder.

Table 3

Search Strings and Databases used for Literature Review

Search strings	
String:	(('DevOps Adoption') OR ('ITIL Adoption') OR ('Agile Adoption') OR ('COBIT Adoption') OR ('TOGAF Adoption') OR ('ZACHMAN Adoption') ('ITSM Adoption') OR ('ITG Adoption') OR ('EA Adoption') OR ('Enterprise Architecture Adoption') OR ('ITG') OR ('COBIT') OR ('ITIL') OR ('EA') OR ('ITSM') OR ('AGILE') OR ('UTAUT') OR ('Adoption Theories') OR ('DevOps') OR ('ITG Critical Success Factors') OR ('ITG CSF') OR ('DevOps Critical Success Factors'))
Criteria:	(PublicationDate > (DATEADD(year,-5,GETDATE()) AND PublicationType IN ('Academic Journals', 'Dissertations', 'Books'))

Table 3 (continued)

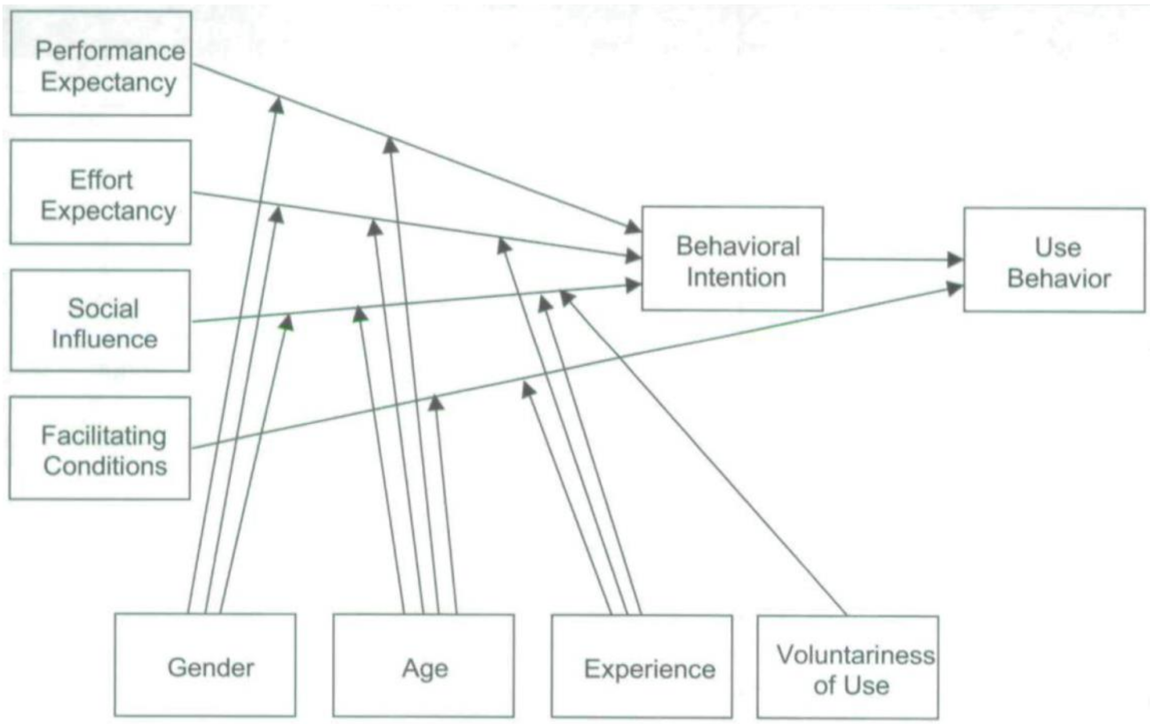
Database	Links	Targeted search area
ACM Digital Library	https://dl.acm.org	Paper title, abstract
IEEE Explore Digital Library	https://ieeexplore.ieee.org	Paper title, keywords, abstract
Science Direct	https://www.sciencedirect.com	Paper title, keywords, abstract
ProQuest Central	https://www-proquest-com	Paper title, abstract

Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) proposed a novel technology acceptance (UTAUT) model, based on eight previous models, in their seminal research. This model was explained in the theoretical framework section above. Figure 2 shows the UTAUT model, which I used as the theoretical framework for this study.

Figure 2

Unified Theory of Acceptance and Use of Technology (UTAUT)



Note. Adapted/Reprinted from "User Acceptance of Information Technology: Toward a Unified View" by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), p. 447. Reprinted with permission.

The UTAUT model was tested and found to outperform previous adoption models Venkatesh et al. (2003). Such model assists IT leaders to understand the likelihood of success when introducing new technologies and helps them understand the drivers for acceptance of such technology. Venkatesh et al. (2016) reviewed the original UTAUT theory by Venkatesh et al. (2003) to understand the existing limitations and improve such model. Furthermore, they proved that UTAUT is the de-facto model used to understand the adoption of technology such as Agile (Hong et al., 2011), online shopping (Lian & Yen, 2014) and e-learning in the workplace (Yoo et al., 2012). Furthermore, the researchers acknowledged the impact of transformational leadership on post adoption and performance of technology. Four recommendations to the existing model were introduced by the researchers, whereby UTAUT2 was used as a baseline model to conceptualize and measure context factors vis-à-vis feature-level factors. UTAUT2 introduced three new constructs (hedonic motivation, price value and habit) and removed the VOL moderator. I considered these new constructs oriented towards technology rather than processes adoption. Therefore, I did not include these constructs in the theoretical model analyzing. For this study, I used the original UTAUT model as proposed by Venkatesh et al. (2003) as the theoretical foundation to understand the drivers for accepting ITG. Furthermore, I analyzed the relationships amongst the various constructs towards ITG adoption.

UTAUT in Information Technology

Anderson (2019) used the UTAUT theoretical framework to quantitatively identify statistical relationships between the UTAUT constructs in the adoption of DevOps. I used a partial least square method for the analysis of data. Anderson demonstrated that PE has a moderately positive relationship with BI to adopt continuous delivery. Conversely, the researcher found that EXP has no effect on BI to adopt DevOps practices. Furthermore, the researcher demonstrated that participants’ perception towards the adoption of continuous delivery practices (DevOps) would be useful in their job.

Participants in the study considered the benefits of such adoption as means to assist them accomplishing tasks more quickly, increasing their productivity, and improve their chances at getting a raise. Anderson (2019) determined that moderators AGE, GDR and VOL had no effect on BI in research pertaining to continuous delivery. However, Gómez (2018) found that respondents lacking any knowledge on ITG may hinder ITG adoption in Ecuadorian public institutions. Hence, it is necessary to measure the VOL to determine how much does prior knowledge affect ITG adoption. Riemer et al. (2020) identified EXP as a factor in the adoption of ITG. The researchers adopted the same theoretical framework as my study, hence it was interesting comparing the results between adoption of DevOps and ITG for DevOps teams. In my research, I investigated whether constructs AGE, GDR and VOL influenced the BI to adopt ITG for DevOps teams.

Shahin et al. (2017) conducted a thematic study to identify strategies, tools, and challenges in the field of continuous practices (DevOps). The researchers found different approaches to improve continuous processes, specifically (a) reduction in build and test time, (b) increased visibility and awareness on build and test results, (c) autonomous continuous testing, (d) monitoring, (e) addressing security and scalability issues in deployment pipeline, and (f) improving dependability and reliability of deployment process. The researcher identified various DevOps challenges and potential KPIs that can be used by an ITG body in determining the state of DevOps within the environment.

Puspitasari et al. (2019) conducted a quantitative study using the UTAUT theoretical framework to determine the factors that affect users in the use of Integrated

Licensing Service Information System and provided recommendations for future implementation of the system. The researchers identified PE as the greatest factors that influences the acceptance and use of Integrated Licensing Service Information System. Krismadinata et al. (2019) used the UTAUT model to quantitatively reveal the factors influencing the adoption of information communication and technology (ICT). The researchers used factor analysis to evaluate the answers of 68 respondents and found that every endogen variable (PE, EE, SI and FC) had a positive effect on BI, thus facilitating the acceptance of ICT. The researchers did not use any moderators, demonstrating the flexibility of the UTAUT model, according to the specific needs.

Chao (2019) used the extended UTAUT theoretical framework to investigate the factors determining the BI to use mobile learning. Researchers use contextual predictors (mobile self-efficacy, perceived enjoyment, satisfaction, trust, and perceived risk) found in the extended UTAUT model, to understand the BI to use a particular technology or system. The researcher used partial least square analysis for the model and hypothesis testing. Chao identified four key findings whereby (a) satisfaction, trust, PE, and EE all had a substantial and beneficial impact on BI; (b) BI was positively associated with perceived enjoyment, PE, and EE; (c) mobile self-efficacy had a significantly positive effect on perceived enjoyment; and (d) perceived risk had a significantly negative moderating effect on the relationship between PE and BI.

Alotaibi (2016) adopted the UTAUT model to quantitatively investigate the adoption factors towards SaaS. The researcher found that acceptance of SaaS was related to PE, EE, SI, FC, and quality of service. Moreover, the GND moderator had no effect on the relationship between SI and BI. Furthermore, Alotaibi indicated that increased AGE, reduced the effect of both EE and SI on BI. This was because elder leaders were found to be more confident in adoption of technology. Similarly, Al hila et al. (2017) found that GND (GDR) was not considered as statistically significant towards the adoption of ITG in e-Training environment.

Bixter et al. (2019) used the UTAUT model as a conceptual framework within a qualitative study, to measure perceived usefulness and perceived ease of use social communication technologies amongst old adults. The data collection instrument included the questionnaire proposed by Davis (1989) and a 7-point Likert scale. The researchers found that the UTAUT model required facilitators and barriers such as trust. Hence the results were inconclusive, although elderly people saw benefits in using social communication technologies.

IT leaders adopting ITG frameworks provide organizations the assurance that their IT initiatives meet required standards and community expectations. Vatanasakdakul et al. (2017) explored the factors influencing the success of ITG adoption. The research model used in this quantitative study was built upon the technology-organization-environment framework (TOE) in conjunction with the Delone and McLean's information system (IS) success model. The PLS method was used to analyze 126 respondents, whereby the population was Australian organizations implementing ITG frameworks. The researchers demonstrated that ease of use, IT innovation, ITG training and external pressure positively affected the success of ITG adoption. Furthermore, ease of use, user satisfaction, external and executive level support were significant towards organizational performance. These findings align with the qualitative research conducted by Aoun et al. (2011) using the same research model.

Aoun et al. (2011) researched the factors determining the success and failure ITG frameworks adoption. The research model used to investigate such factors was based on seminal work by Tornatzky and Fleischer (1990) and Delone and McLean (2003). The same model was used by Vatanasakdakul et al. (2017) for the same research question using a quantitate approach. The model posits that organizations adopting ITG frameworks are likely to perceive positive organization performance (PE) and positive user satisfaction (BI) based on (a) strong top management support, (b)internal ITG expertise, (c) ITG training, (d) organizations whose competitors adopted ITG frameworks, and (e) firms having access to external ITG support and/or pressured by external factors (industry, government, or compliance). Technological, organizational, and environmental contexts were integrated in the research model to determine the user satisfaction and perceived organizational performance. These constructs align with the UTAUT model specifically PE, BI, EE, and FC.

DevOps

DevOps is aimed at removing the barriers between development and operation teams through coordination and automation of provisioning, release management. Bianchi et al. (2020) found that the adoption of State-Gate principles had a negative association towards speed and cost. Conversely, the adoption of sprints had a positive association to product quality and efficiency. The combination of both methodologies has contrasting results depending on the principles. Software developers consider agile methodology as the appropriate tool for new product development because it may lead to a reduction in product delivery times. DevOps teams are built upon agile notions whereby uncertainty is accepted and accommodated through the development and delivery lifecycle. Zaitsev et al. (2020) explored the coordination mechanisms adopted by organizations within Agile development projects, specifically related to coordination artifacts. The results identified distinctive artifacts that provide different project coordination support. Foundational artifacts were used in the initiation process for reconciling priorities, whereas projective artifacts were used in the discovery phase to consolidate expectations. Indicative and exposition artifacts were used in the development phase to manage the producer/consumer expectations and coordination tasks.

The role of DevOps within an organization is to broaden the collaboration amongst different teams to increase agility of software delivery. The survey paper by Katal et al. (2019) identified the required cultural and organizational changes, as well as tools necessary to achieve DevOps transformation. Cultural shift, through the identification of shared goals and empowerment, is a key requirement to the adoption of DevOps. Additionally, the use of Quality Assurance (QA) teams is necessary to measure the success of products and DevOps teams. These changes cannot be achieved without (a) organizational transformation through formation of new teams and (b) tools including collaboration, project management, issue tracking, monitoring, and configuration management. Multi-product organizations need to adopt Lean principles to effectively used DevOps practices. Having different DevOps teams, supporting functions (Product Owners, QA) and tools hinders the break-up of silos and increases costs. ITG practices ensure that holistic and self-organizing teams can use common functions and tools amongst different products, through shared knowledge and effective monitoring and improvement initiatives.

Wiedemann et al. (2020) used the grounded theory to propose an IT alignment model, based on eight case studies of DevOps implementations in various industries. A tripartite model was proposed comprising of (a) building individual componentization through silent releases, containerization, and modifiable infrastructure, (b) enabling of integrated responsibility through agile extension, process automation and product orientation, and (c) integrating multi-disciplinary knowledge through competency broadening, problem ownership, and knowledge sharing. Misalignment in DevOps can arise quickly and can have a negative effect on performance. IT alignment models such as the one proposed by Wiedemann et al. (2020) may be translated into structured processed as an ITG framework, whereby IT leaders ensure that the mechanisms in this tripartite model are governed appropriately.

Perceived benefits of DevOps include improved (a) delivery speed of software, (b) productivity in operations through improved communication, reduction of bureaucracy and reduction of human intervention and errors in the delivery, (c) quality and (d) organizational-wide DevOps culture. Lwakatare et al. (2019) reviewed the implementation strategies for DevOps adoption in small and medium service development organizations. Successful DevOps implementation can be measured by various KPIs including (a) duration between releases and (b) minimum deployment errors. This study found that (a) effective DevOps is achieved by assigning deployment rights and control to development teams, (b) software toolchain and support is a key factor in the acceleration of delivery (c) contextual variables, such as manual approvals by the product owner, influence delivery speed to production and (d) new skills require a high degree of training.

Organizations are adopting DevOps processes to foster increased collaboration amongst development and operations teams, resulting in improved quality and efficiency both at development and support phases. Zarour et al. (2020) measured DevOps adoption level in 7 Saudi Arabian organizations by utilizing the Bucena capability maturity model. The factors within the capability model encompass 4 dimensions (a) technology, (b) process, (c) people, and (d) culture. The researchers demonstrated that the organizations struggled in (a) data management, (b) software configuration management, (c) issue tracking, (d) development, (e) project management, (g) documentation, (h) organization of teams, (i) upskilling, (j) culture transformation, and (j) innovation drivers. Similarly, Zdun et al. (2020) reviewed emerging trends and challenges in DevOps and microservice APIs. The researchers identified 4 key challenges (a) service identification and design,

(b) API technologies, management, and innovation, (c) service deployment and operation, and (d) service implementation.

A critical step in achieving an optimized DevOps maturity, requires self-adapting governance that is capable to adapt to changes, whilst utilizing formal communication channels and leverage automation. Radstaak (2019) proposed a DevOps maturity model to provide a validated measure on the capabilities of the DevOps function within organizations. The premise of such model was to (a) guide organizations achieving an optimized level, whilst (b) demonstrating other department actionable items towards achieving a DevOps culture. The model was built from the CMMI model and other constructs obtained from interviews with DevOps experts. Validated of the artifact was achieved through multiple case studies.

Waseem et al. (2020) reviewed 47 studies published between January 2009 and July 2018 related to the adoption of microservices architecture (MSA) in DevOps environments. The empirical research identified three recurring themes related to DevOps teams specifically (a) development and operations, (b) tooling and support strategies, and (c) MSA migration EXP. The researchers demonstrated that quality attributes are positively affected by MSA. Furthermore, the researchers identified DevOps challenges introduced by MSA such as (a) resource management, (b) set-up of cross-functional teams, (c) monitoring, (d) deployment, (e) testing, (f) implementation, (g) design, and (h) requirements. The identification of such challenges provides ITG within DevOps environments specific focus on areas to control, evaluate and monitor.

The use of appropriate tools allows engineers to manage products effectively within DevOps environments. Large organization rely on application lifecycle management (ALM) software, such as Atlassian, to govern development and maintenance of software products. Tüzün et al. (2019) investigated the adoption of ALM tools to increase software development productivity and reduce maintenance costs. The case study found that ALM 2.0 addressed shortcomings found in ALM 1.0, specifically related to complex processes and tools integration within large enterprises. The expected gains included operational, organizational and production benefits. The functionality provided by such tools needs to be leveraged by a competent governance team to ensure that product delivery meets the necessary expectations.

Perkusich et al. (2020) reviewed 103 primary studies pertaining to intelligent software engineering techniques in agile software development (ASD) organizations. The key drives in the use of intelligent techniques are (a) effort estimation, (b) requirements prioritization, (c) resource allocation, (d) requirements selection, (e) requirements management, and (f) decision making. The researchers identified factors that elicit the use of intelligent techniques in software development by accessing data from versioning control such as Git, build management systems such as Jenkins and project management tool such as Jira. ITG in conjunction with intelligent techniques ensure that products are delivered using the optimal resources and prioritizing the requirements as needed by the end users.

A key pillar in DevOps environments is the automation of development and operational processes, including the provisioning of infrastructure and network automation. Khumaidi (2021) demonstrated the practicality of Ansible in a DevOps context to facilitate server management. The experiment involved a management server, 3 remote servers and network switches. The implementation of automation was achieved through SSH cryptography, YAML and Python in conjunction with Ansible. Various playbooks were used to validate the effectiveness of remote and centralized management including server access, disk partitioning, servers' uptime, and user logins. Network automation allows DevOps teams to automate policies in the network as the infrastructure grows. This facilitates management and security of product delivery and hosting.

Leite et al. (2020) developed a DevOps conceptual map, correlating DevOps automation tools with such actors and processes. Fundamental concepts of DevOps include (a) process, (b) people, (c) delivery and (d) runtime, whereas DevOps toolsets include (a) knowledge sharing, (b) source code management, (c) build process, (d) continuous integration, (e) deployment automation and (f) monitoring and logging. These concepts allowed the researchers to investigate the DevOps challenges amongst engineers, manager, researchers, and the organizations. Implications for DevOps engineers include (a) technical architecture, (b) rollback, (c) inhibitors for high-frequency delivery, (d) testing, (e) legacy systems, (f) communication, (g) learning, (h) pipeline maintenance, (i) incident handling and (j) security. Manager's challenges include (a) adoption of lean principles, (b) DevOps adoption, (c) assessment, (d) training, (e) performance and (f) culture. The challenges IT leaders face in DevOps environments were also found in other studies such as the adoption of lean principles (Galup et al., 2020), trust (Masombuka, 2020), measurement (Luz et al., 2019), and performance (Trubiani et al., 2019).

Trubiani et al. (2019) used a quantitative design to identify the uncertainties affecting DevOps teams and understand the relationships of such uncertainties towards PE (PE). Deployment infrastructure, software versions and code changes, configuration parameters, workload fluctuations as well as monitoring and sensor accuracy were identified as key design decision towards mitigating uncertainties. Furthermore, bottom-up or top-down approaches can be used in the implementation, based on the knowledge of existing uncertainties. DevOps teams need to manage uncertainty related to workload fluctuations (WFs), resource availability and upgrades as these negatively affect performance. ITG in DevOps teams need to identify such uncertainties and implement appropriate strategies whilst ensuring adequate monitoring.

Mishra and Otaiwi (2020) focused their qualitative study on the relationship between software quality and DevOps characteristics. The identification of DevOps and Software quality practices were identified through an empirical literature review of 35 peer-reviewed articles. DevOps characteristics identified in the study include (a) culture, (b) sharing, (c) fast feedback, (d) automation, (e) CI/CD, (f) measurements and (g) software architecture. Such features relate to software quality being (a) flexibility, (b) testability, (c) usability, (d) efficiency, (e) maintainability, (f) portability, (g) reliability,

(h) security, (i) reusability and (j) interoperability. Quality is a critical factor within product development that can be addressed through DevOps, since it focuses on deployment speed, frequency, and quality through development and operational activities.

Masombuka (2020), conducted a sequential mixed method study based on the Information System Development Model to develop a framework for the adoption of a DevOps culture through the identification of critical success factors. The results found that open communication, roles and responsibilities, respect and trust are critical success factors that constitute a DevOps culture. Masombuka highlighted the importance of adopting of DevOps culture to achieve agility. Hence, IT leaders need to control and monitor such critical success factors towards DevOps adoption.

Collaboration and monitoring are key elements towards a DevOps culture. These elements were central findings in the qualitative study conducted by Luz et al. (2019). Insights from semi structured interviews within 15 organizations allowed to researchers to build a DevOps adoption model based on the Grounded theory. This model was validated through a case study whereby a collaborative culture was identified as a key concern in the adoption process. Hence, ITG should elicit collaboration amongst the various stakeholders, whilst continuously improvements can be achieved through monitoring of appropriate KPIs. Hemon et al., (2019) investigated collaboration and soft skills necessary to manage DevOps teams, through a case study. Three transitionary phases were identified for DevOps comprising of (a) agile, (b) continuous integration and

(c) continuous delivery. The researchers suggested that adoption of a DevOps culture increases as collaboration and soft skills increase. Such skills include communication, responsibility, and teamwork.

The lack of research pertaining to knowledge-sharing practices within large-scale DevOps was researched by Hemon et al. (2020) through 106 interviews in a multinational company utilizing DevOps methodology. The researchers showed (a) the need for a strong cross-functional collaboration amongst Dev and Ops, (b) the presence of multiple environment divergence leading to specialized teams, (c) automation led to a loss of global vision or knowledge, (d) knowledge sharing was limited to hierarchical organizational structure, and (e) limited sharing in outsourcing of Dev and/or Ops. Mature DevOps teams engage in dynamic role rotations (DRR), tech-talks (TTs), backlog-grooming and sprint planning (HUGP) and joint-reflection sessions (The circle) comprising of all stakeholders to mitigate to such challenges.

Hart and Burke (2020) used data from 57 organizations within the Forbes Global 2000 and Fortune 500, using a partial least squares structural equation model (PLS-SEM) to analyze the DevOps IT alignment model. Hart and Burke demonstrated that IT organizations utilizing DevOps methodology, experienced an increased level of IT alignment through continuous integration and knowledge sharing. Hart and Burke (2020) used a quantitative design to determine the relationship between ITG and DevOps methodology whilst it identified key DevOps functions improving ITG. These functions included continuous integration (CI), knowledge sharing (KS), subunit size, company tenure and DevOps EXP.

Hemon-Hildgen et al. (2020) investigated the effects of DevOps towards job satisfaction, risks, and work conditions. This was achieved through 59 interviews in 12 agile and DevOps teams within the same organization. The conceptual framework for the study was based on the job design characteristics theory and Herzberg's job satisfaction theory. The researchers demonstrated that DevOps in conjunction with agile provides greater job satisfaction, compared to agile alone. However, the introduction of DevOps amplified risk related to (a) jobs exposed to external criticism, (b) lack of organizational support, (c) time management between project and operations, and (d) hiding of functional defects. The work by Hemon-Hildgen et al. (2020) demonstrated that DevOps roles had positive SI, whereby professionals were willing to work in DevOps teams. The risks arising from the adoption of DevOps need to be mitigated through adequate risk management. ITG was found to be effective in managing IT related risks (Edirisinghe Vincent & Pinsker, 2020), which also applies to DevOps.

Fox (2020) examined the challenges of ITG to accommodate DevOps in the United States Department of Defense. The researcher found that DevOps methodology has strong implications for ITG, specifically in the areas of strategic alignment, cost control, risk management, and cultural implications. The purpose of this study may extend the body literature, whereby a different industry was used (multiproduct organizations) to determine the adoption of ITG in DevOps environments.

IT Governance

As organizations embrace agile methodologies, ITG needs to shift from a relatively static structure to a dynamic, open, and transformational system that allows continuous changes to its mechanisms and processes. Vejseli et al. (2018) reviewed how organizations transformed their ITG frameworks to meet the demand for agility. 33 leaders within the banking industry from the DACH region provided the necessary data to understand the necessary changes. The agile ITG dimensions identified in the study were classified in 3 categories specifically (a) relational mechanisms, (b) processes, and (c) structures. Such agile dimensions included (a) transformation leadership, (b) adoption of lean structures and mechanisms, (c) cross functional training, (d) innovation and prioritization processes, (e) innovative KPIs, (f) delegation of decision making, (g) lessons learned sessions, and (h) interdisciplinary small teams. Gersick (1991), Romanelli and Tushman (1994) and Greiner (1997) explained how organizational development followed the punctuated equilibrium theory, whereby organizations continuously transitioned from a state of (a) stability to (b) adjustment and vice-versa. This cyclic movement is necessary to optimize and adapt to changes.

The exploration of ITG structures and processes, which provide competitive advantages to DevOps teams was researched by Wiedemann (2018), through interviews in six different organizations that implemented DevOps teams. The most important ITG processes identified by IT leaders in DevOps teams are (a) requirements management, (b) software development, (c) quality assurance, (d) test management, (e) software operation,

(f) support, (g) continuous integration / delivery / deployment, and (h) establishment of SLAs. Wiedemann demonstrated that DevOps teams either utilize Kanban or SCRUM as an agile methodology. Furthermore, DevOps teams consist of software developers or software engineers, whereas in most of the cases (5 out of 6) a product owner was part of the team. The outlier team worked with several product owners from different business sections. In a multiproduct environment, a cross-functional approach may result in improved resource optimization. The researcher showed that DevOps teams had a great autonomy and report to a single team lead or the CIO. Organizations possess DevOps maturity tend to utilize flat hierarchies to increase agility.

By undertaking an analysis of product ownership in large scale, cross-border software development over 8 years of research from 93 practitioners in 21 UK organization Bass & Haxby, (2019) demonstrated that practitioners used their own scaled agile approach. Furthermore, the researchers identified three additional groups of activities, specifically scale, distance, and governance. Beecham et al. (2021) demonstrated that alignment is a major risk in global and large-scale software development teams. Irrespective whether the organization adopted disciplined agile development (DAD) or scaled agile framework (SAFe) the researchers highlighted the importance of ITG adoption. This section of the literature review determined how organizations adopt ITG.

The pragmatic approach allows a researcher to determine that an effect is the result of an action. The tensions between innovation and operations are manifested in

DevOps environments whereby developers continuously deliver revised products and engineers maintain the product. ITG is an adequate tool to mitigate exploration and exploitation tensions by allocating resources based on the pragmatic ambidexterity approach. Such approach is suitable within an agile environment, such as DevOps teams, where emphasis on both innovation and operations need to be carried out concurrently. The model driven ITG framework (MoDrIGo) proposed by Wautelet (2019, allows organizations to adopt ITG throughout IT business structures. This model was validated through a case study whereby it was found that such model lacked characteristics including responsibility, performance, and conformance of IT services. The exploration and understanding of factors towards the adoption of ITG is hence necessary prior to the selection of a specific model.

Chau et al. (2020) investigated the effect of alignment on performance by analyzing data from 87 organizations using a moderated polynomial. The researchers demonstrated a positive relationship of ITG on organizational performance, thus aligning with this study's problem. Organizations with more effective ITG are not likely to struggle with mild misalignment but may suffer more damaging effects from severe misalignment. Moreover, the researchers provided a statistical recommendation (non-linearity) for quantitative research, as well as an overall baseline of findings upon which to engage in the final discussion.

The lack of literature pertaining to the relationship between the adoption of ITG enablers and IoT implementations, motivated Henriques et al. (2020) to conduct a systematic literature review of 44 studies, whereby various ITG enablers were identified. These included (a) principles, policies, and frameworks, (b) services, infrastructure, and applications, (c) culture, ethics, and behavior, (d) processes, (e) information, (f) people, skills, and competencies, and (g) organizational structures. The ITG recommendations provided by Henriques et al. (2020) in the context of IoT, were found in other studies. The notion of trust was discussed by Masombuka (2020), coordination was highlighted by Zaitsev et al. (2020), the importance of roles was discussed by Galup et al. (2020), and Khumaidi (2021) examined the need for adequate tools. These studies demonstrate that ITG enablers are similar in different domains such as DevOps and IoT.

Najjar et al. (2020) used non-probability sampling within the financial sector in Saudi Arabia to quantitatively identify challenges of ITG in the financial sector. The researchers identified barriers and challenges of ITG, specifically (a) lack of understanding of the relevant regulations, (b) inadequate regulations, (c) lack of persuasive communication, (d) lack of commitment from top management, (e) lack of financial and human support, (f) lack of perspective vis-à-vis business and IT integration and (g) lack of business orientation from IT staff. The mitigation strategies identified by Najjar et al. (2020), allow ITG to enhance operations by simplifying the consumption of IT, within the financial industry.

Karamitsos et al. (2020) identified the need of DevOps practices for the development and support of machine learning. However, the establishment of a DevOps culture requires the introduction of KPIs including (a) automation of processes, (b) measurement of KPIs, (c) sharing feedback and (d) knowledge sharing These findings tie into the study carried out by Singh et al. (2020) whereby tensions between development and operations were identified. Singh et al. (2020) examined a health organization's response to technological, regulatory and demand changes over 15 years. The organization managed the friction amongst innovation and operations through the combination of pragmatism and ambidexterity management, by means of structured ITG. The researchers used sequential ambidexterity to alternate innovation in IT with operations over the years. A mixture of sequential, structural, and contextual ambidexterity was used to manage technological, regulatory and demand changes.

Zhen et al. (2021) examined the antecedents towards enterprise agility and proposed a model comprising ITG processes, top management support and IT ambidexterity (exploration and exploitation). The model was validated using correlational analysis in 326 Chinese organizations. The results showed that top management support has a positive relationship with ITG processes specifically (a) structural, (b) process-based, and (c) relational mechanisms. Furthermore, process-based, and relational governance have a positive relation with IT exploration and exploitation. Lastly, the researchers demonstrated that IT ambidexterity positively influenced organizational agility. Organizational agility allows firms to adapt to rapid market changes that dictate modification to strategies and actions. By means of a quantitative study, the researcher revealed the positive influences brought by ITG in managing IT ambidexterity, reinforcing the findings by Singh et al. (2020). Multi-product delivery organizations need to adapt to market and technology changes to ensure competitiveness.

Continuous delivery challenges are further highlighted as organizations transition to microservice architectures. The resolution of such issues is the responsibility of DevOps teams. Debroy and Miller (2020) conducted a case study in a small organization, which transitioned from a monolithic to a microservice-based architecture, to explore the challenges and solutions in the CI/CD process during the changeover. Reconciliation of dependencies among microservices was a challenge that was mitigated through the containerization of build/release agents. Retention of short build and release times was resolved with custom images for build and release Agents. Ensuring low infrastructure costs was accomplished with resource orchestration, whilst parallelizing builds was achieved by the adoption of Infrastructure as Code (IaC). The researchers show that unless resolution activities are linked, codified, and monitored at a holistic level inside a governing body, DevOps teams supporting diverse products would have a detrimental impact on efficiency, delivery timelines, and costs.

Wiedenhöft et al. (2019) used the organizational citizenship behavior (OCB) theory to understand the effects of ITG institutionalization on civil servants' behavior through literature, focus group and interviews. The results were validated through a descriptive-confirmative study whereby the feedback from 173 respondents was analyzed through PLS-SEM. This multi-method study found that ITG institutionalization encouraged individual behavioral changes as defined by the OCB constructs, specifically

(a) interpersonal harmony, (b) conscientiousness, (c) individual initiative, and (d) identification with the organization. The positive relationship between ITG institutionalization on civil servants' behavior suggests that DevOps team may also be positively impacted when adopting ITG.

The inter-functional relevance of ITG is demonstrated in its various utilizations. Over the last two years the need to adopt digital contact-tracing during the COVID-19 pandemic prompted IT leaders and researchers to look at ITG towards successful adoption of such technology. Riemer et al. (2020) identified 5 factors influencing ITG approaches at a societal level being (a) risks, (b) EXP, (c) culture and values, (d) executive support and (e) trust. Culture and values align with SI, whereas perceived risk can be used as a moderator (Chao, 2019). Trust and executive support were identified as key factors in adopting ITG (Bixter et al., 2019; Henriques et al., 2020; Masombuka, 2020; Najjar et al., 2020; Zhen et al., 2021). Riemer et al. (2020) validates the relevance of the UTAUT constructs, whilst it also demonstrates the importance of ITG in the adoption of technology.

Al-Marsy et al. (2021) explored the adoption of Health Information Systems (HIS) and proposed a model that can be used by IT leaders, towards such a transformational initiative in the health industry. The model used three dimensions, specifically (a) financial performance and cost, (b) IT operations excellence and DevOps, and (c) security, governance, and compliance. Challenges in the DevOps dimension include microservice architecture (FC), automation (PE), complexities (EE), skillset

(FC), and EXP. Conversely, challenges in the governance domain include shared responsibility and retention of compliance and legislation such as HIPAA and HITECH. The use of DevOps in conjunction with governance facilitates the implementation of HIS within health facilities. The challenges identified in this study align with constructs of UTAUT, specifically PE, EE, and FC.

Erasmus and Marnewick (2021) investigated the perceptions and implementations of ITG. Q-methodology and inverted factor analysis drove the mixed-methods study whereby 35 statements were presented to 13 participants to sort according to importance. These statements were derived from extensive literature review. The results highlighted 4 perspectives in relation to directing and monitoring activities, being (a) financial management, (b) prioritizing skills and benefits, (c) enterprise architecture, (d) strategic emphasis. ITG provides strategic alignment through the management of costs, resources, stakeholders, prioritization, communication, architecture, and security. These social perceptions were identified and discussed in other studies (Greene, 2020; Nachrowi et al., 2020; Zhang et al., 2019b).

ITG adoption can be adopted either at managerial or board level. Caluwe and De Haes (2019), reviewed the state of research domain within board level ITG. Existing literature gap included (a) uncertainty about contingency factors (internal and external success factors), (b) gap between prescriptive (best practice structure methods) and descriptive (existing structure methods) research and (c) uncertainty about the consequences of not involving board-level ITG. The researchers determined that board level ITG improved organizational performance, whilst allowing organizations to manage the business risks. Few boards involve ITG due to (a) lack of IT expertise, (b) motivational factors, (c) age, (d) lack of IT role understanding within the organization, and (e) lack of IT information. ITG should include board members since they are accountable for strategy and control. The involvement of CIOs or CTOs in ITG teams is necessary to onboard the board.

Managerial-level ITG focuses on the IT decision-making structures and contingencies that determine the best way to implement ITF. There are different forms of factors contributing to the adoption of ITG. Brown and Grant (2005) reviewed the literature and determined that ITG mirrors the daily activities of decision-making rights, input rights and accountability measures. The existing ITG literature followed two streams related to (a) forms and (b) contingency analysis. ITG can be adopted in various forms, specifically (a) business monarchy, (b) IT monarchy, (c) feudal, (d) federal, (e) IT duopoly and (f) anarchy. ITG contingency factors comprise of (a) corporate vision, (b) corporate strategy, (c) firm structure, (d) culture, (e) strategic IT role, (f) IT senior management, (g) satisfaction with IT management, (h) satisfaction with use of IT, (i) strategic plan of current and future applications and (j) status of control for approval and prioritization.

Scalabrin Bianchi et al. (2021) used the Design Science Research (DSR) as the conceptual framework to identify ITG practices relevant to universities. 10 interviews with IT Directors in different universities allowed the researchers to propose a model that was validated by experts. The researchers demonstrated that amongst the most important ITG practices include (a) the establishment of an IT strategy committee, (b) strategic information systems planning, (c) use of ITG frameworks, and (d) ITG knowledge management. The researchers implied that ITG practices can be extended according to specific contexts such as multiproduct DevOps teams.

Ebert et al. (2020) reviewed ITG strategies adopted by organizations. The researchers determined that (a) ISO, (b) COBIT5, and (c) ITIL are used by organizations to ensure (a) strategic alignment, (b) value delivery, (c) resource management, and (d) performance management. Furthermore, organizations used reporting tools to manage ITG, including ControlCase IT-GRC, IBM Open Pages, ServiceNow GRC and Alfabet EAM.

COBIT

Greene (2020) conducted a qualitative Delphi study and presented an ITG framework that was validated in a large manufacturing US organization. Furthermore, Greene identified challenges that organizations encounter due to a lack of governance for DevOps teams. COBIT 5 was identified as an appropriate conceptual framework to implement ITG for DevOps teams. The domains in COBIT 5 are (a) align, plan, and organize (APO), (b) build, acquire and implement (BAI), (c) deliver, service and support (DSS), and (d) monitor, evaluate, and assess (MEA) and (e) evaluate, direct and monitor (EDM). Hartono (2020) focused specifically on the EDM domain in his case study.

ITG for DevOps teams increase information systems’ efficiency, quality, and value to the business. Software development and delivery decisions are critical factors in DevOps teams. Organizational structures need modification to achieve a DevOps culture whereas customers should be decision-makers in issues that impact delivery of products. Lack of governance can result in a scarcity of communication between customers and DevOps affecting continuous delivery. Moreover, lack of ITG may remove the opportunity to innovate due to lack of standard processes and structures.

The usefulness of systems or processes is based on the users' perceptions. y Greene (2019), used the grounded theory to examine the perceptions of IT Internal auditors in insurance companies regarding the factors influencing the controls within COBIT's DSS domain towards the protection of confidentiality of consumer personal identifiable information (PII). Greene showed that management of security risk required (a) governance, (b) risk management, and (c) compliance. Additionally, the implementation of controls practices such as DS2, DS5, and DS11 was identified as critical factor in achieving governance through guidance, performance, awareness, and skills. Furthermore, Greene (2019), identified the need to understand the infrastructure in terms of data, critical infrastructure and thirty party entities. Security is a core pillar in IT systems and hence its relevance in ITG cannot be discounted. IT leaders in DevOps environments need to ensure that security risk management is undertaken through implementation of control practices and understanding of the infrastructure.

Resource optimization is a common challenge in IT organizations. Such challenge is further highlighted in DevOps environments where engineers need to wear different heads in operational and development activities. ITG processes may assist IT leaders to manage their resource more efficiently. Sihotang et al. (2020) used the COBIT 5 framework to address this challenge. 16 processes within the COBIT 5 framework were used to improve the organization's resource management. The processes are EDM02 (Ensure Benefits Delivery), EDM04 (Ensure Resource Optimization), APO01 (Manage the IT Management Framework), APO03 (Manage Enterprise Architecture), APO04 (Manage Innovation), APO07 (Manage Human Resources), APO08 (Manage Relationships), APO10 (Manage Suppliers), APO13 (Manage Security), BAI01 (Manage Programs and Project), BAI02 (Manage Requirements Definition), BAI04 (Manage Availability) , DSS01 (Manage Operations), DSS03 (Manage Problems) DSS04 (Manage Continuity) and MEA01 (Monitor, Evaluate and Assess Performance and Conformance). Sihotang et al. (2020) demonstrated that ITG activities address various organizational issues such as resource optimization.

Hartono (2020) conducted a case study with an Indonesian ISP provider, to evaluate ITG capabilities and propose optimization of IT assets using such framework. COBIT 5 was used to measure ITG capability through 4 ratings being not achieved (N), partially achieved (P), largely achieved (L) and fully achieved (F). This rating scale was set by the ISO / IEC 15504 standard. Existing literature agree that the adoption of COBIT 5 is a large and time-consuming project. This suggests that a phased approach (by domain) may be more successful in the adoption of ITG.

Bounagui et al. (2019) reviewed existing IT models, specifically (a) ITIL, (b) COBIT and (c) ISO 27001/2 and proposed a novel management and governance framework focused on cloud computing. Such a unified model requires three different methods being (a) evaluation, (b) integration and (c) homogenization. The three frameworks were evaluated based on (a) Cloud Management, (b) Risk Management, (c) Information Systems and (d) Service Level Agreements. The researchers demonstrated the strengths and weaknesses of each framework when applied on the four dimensions above. Thus, a unified framework covers each domain in a more holistic and appropriate manner. Bounagui et al. (2019) demonstrated that existing frameworks are not exhaustively adequate to manage and govern cloud computing. The emergence of DevOps occurred during the acceleration in the adoption of cloud computing. Hence the capabilities of such frameworks to govern DevOps teams needs to be investigated. Organizations use different frameworks to direct, evaluate and monitor DevOps teams, however it is not clear whether such implementations are exhaustive.

Patterson (2020) used the business model canvas and mapped the business imperatives to COBIT 5. This study focused on the IT architecture process, which can be designed to support the business objectives. The researcher identified business requirements, specifically (a) performance, (b) customer-centricity, (c) low costs, (d) diverse products, (e) reduction of delivery times. (f) product-centricity and (g) innovation. These requirements were aligned to the technology architecture by implementing COBIT 5 framework in a case study. A major contributing factor in the failure of IT projects is attributed to miscommunication between senior management and IT specialists. Furthermore, IT gaps and misalignments accentuate the failure rate of IT initiatives. COBIT 5 can be adopted to identify business requirements whilst minimizing IT gaps and misalignment, thus ensuring project/product success.

Edirisinghe Vincent and Pinsker (2020) used the organizational strategy information system and COBIT framework to explore the relationships of the various activities in the field of IT risk management (ITRM). Through a survey with senior IT executives, the researchers propose a holistic model for ITRM practices. The researchers identified four ITRM activities, specifically (a) ITG, (b) communications, (c) operations, and (d) monitoring. The operations domain within the DevOps culture is often overlooked, whereby research is focused predominantly on the development area. However, the researchers demonstrated the importance of managing operations. Furthermore, the ITRM activities identified by Edirisinghe Vincent and Pinsker (2020) highlight the necessity for a holistic ITG strategy within a DevOps environment, rather than focusing on functions.

Vugec et al. (2017) investigated the reasons, ways, and differences in the adoption of COBIT amongst organization in the financial sector. A longitudinal multi-case study approach was used. The research instrument used for this study included COBIT mechanisms in five different ITG components, specifically (a) IT-business alignment, (b) IT contribution towards value creation and delivery, (c) IT risk management, (d) IT resource management, and (e) IT performance measurement. The researchers demonstrated that case studies increased their COBIT maturity levels over 5 years, however the level and speed differed. The factors that affected the speed of maturity level was dependent on top management support, specifically the CIO role and its relationship with the CEO. IT audits were also beneficial to increase the maturity level and speed due to awareness and shortcomings.

The relationship between COBIT 5 adoption and IT goals achievement was researched by De Haes et al. (2016). The researchers demonstrated that the achievement of IT goals positively related to the achievement of enterprise goals. Furthermore, De Haes et al. (2016) showed that organizations adopting DSS (Deliver, Service and Support) domain processes, as mandated by COBIT5, achieved better results in IT and enterprise goals. Furthermore, the investigation indicated that management and governance implementation success dropped when business and board support was required. Moreover, De Haes et al. (2016) found that albeit small and medium organizations (SMEs) have a lower perceived mean implementation maturity, they share the same perceived achievement of IT and enterprise goals with large enterprises, except for the financial dimension.

"*DevOps is about good development practices that continually deliver product features (Agile) effectively with minimal wasted efforts (Lean) which are overseen by good governance controls (ITSM)*" (Galup et al., 2020, p. 48). The widely accepted notion that *DevOps = Agile + Lean + ITSM* prompted Galup et al. (2020) to develop a regression model to determine the salary of IT professionals having the relevant skillsets.

The Human Capital Theory was applied as the theoretical foundation to determine compensation benefits of IT professionals having Agile, Lean and ITIL skills and the estimated benefits. The researcher’s findings implied that lack of agile, lean and ITIL skillset negatively affect the implementation of a DevOps culture.

The adoption of COBIT 5 pose certain challenges since adoption of such framework is a large and complex project, which may take years for full maturity. Furthermore COBIT 5 adoption suffers from lack of top management support, resistance to change and scope misalignment. Specifically, adoption of ITG in agile environments such as DevOps require tailor-made implementation models. Amorim et al. (2020) adopted Scrum methodology in the implementation of COBIT structures. The Design Science Research Methodology (DSRM) was used to observe the results in two different case studies. The researchers used semi-structured interviews and demonstrated that such model positively affected ease of perception, ease of use, utility for the organization and people, and goal efficacy.

ITIL

ITIL is a process-based framework focused on IT production and quality. This framework may be used to govern production teams like DevOps. The understanding of critical factors in successful ITIL implementations, prompted Blumberg et al. (2019) to undertake a qualitative multiple-case study. The socio-technical systems (STS) were used as the conceptual framework to explore ITIL adoption strategies within eight large organizations. The researchers found that the adoption of ITIL required changes to the four components of STS, being (a) people, (b) organizational structure, (c) processes and (d) tools. Changes to one component affected other components whereas effort on each component is not equal. The researchers demonstrated that extensive transformation is required for a successful adoption of ITIL within organizations.

Winkler and Wulf (2019) posited that ITSM capabilities are positively affected by IS effectiveness, through the alignment of the IS function with the organizational IS strategy. A survey utilizing 256 participants as the sample size was used to validate the above-mentioned hypothesis through a service-dominant theoretical framework. The researchers confirmed that ITSM capability is mediated by IS-business alignment and reinforced by IS strategic conservativeness. Organizations with conservative IS strategies tend to benefit most from the adoption of ITSM practices. Conversely, agile-driven organizations need to ensure that ITSM practices does not conflict with flexibility and innovation. The adoption of ITSM practices is aimed to improve IS effectiveness through alignment between IS strategy and function, whereby agile driven organizations need to find the right balance between innovation and rule-based practices whilst focusing on processes such as service level management, change request and incident management.

Zaydi and Nassereddine (2019) investigated the adoption of SecOps in ITSM activities through semi-structured interviews with multiple organizations in the MENA region. Stakeholder participation is a recognized practice and widely used by ITSM team to improve delivery of products. Furthermore, testing and deployment activities need to be included in ITSM activities to manage incidents and ensure agility and security.

Additionally, activities such as feedback loops between development, security and operations, and process standardization are encouraged. Security needs to be integrated in the continuous delivery framework to reduce security risks. ITG brings the security voice on the table, whilst ensuring feedback loop to safeguard that the continuous delivery pipeline is build and supported using best practices.

Dayal and Rana (2019) investigated the ITIL processes that are mostly used in Indian IT industries. These processes where categorized as (a) technical including IT Continuity and Service Level management, (b) operational including problem, incident change, configuration, and release management, and (c) other processes. Project management, implementation of service management, application management, ICT infrastructure management and security management were identified; however these were not categorized neither as technical nor operational due to their cross-dependency and mechanics. COBIT 5 has 5 different domains to effectively govern IT environments. Consequentially, the governance of DevOps teams requires various processes and specific ITIL processes address such requirements. The use of ITIL's technical, operational, and cross functional processes may improve quality of services. The combination of ITIL and COBIT was researched by Nachrowi et al. (2020), whereby such a convergent model addresses management and service processes.

Nachrowi et al. (2020) conducted a case study in the educational field, to determine the satisfaction level of service applications. Improvements were based on the recommendations of COBIT 2019 and ITIL 4 frameworks. The researchers identified five different domains to ensure governance and management of IT. These domains are (a) evaluate, direct and monitor, (b) align, plan, and organize, (c) build, acquire and implement, (d) delver, service, and support and (e) monitor, evaluate and assess. The results of the case study demonstrate shortcomings in all domains, especially in managing risk, changes, and performance monitoring. Furthermore, security is considered the biggest IT threat to the IT provisioning. The adoption of COBIT 2019 and ITIL4 processes allow organizations to improve their governance and management objectives.

The relationship between leadership and adoption of DevOps practices was analyzed by Maroukian and Gulliver (2020) through 30 interviews in 9 industries within 10 different countries. The researchers explored the transitioning challenges from highly structured service management processes to DevOps practices. ITIL was identified as the most frequently adopted framework in DevOps environments, enabling change management, release and deployment management, service level management, incident management and service catalog management. ITSM practices, specifically ITIL may be extended to DevOps practices to ensure successful adoption of continuous delivery.

Joshi et al. (2018) used a field survey amongst 124 organizations to understand the composition of information technology governance through the constructs of ITG maturity and IT strategic role. The researchers reviewed the annual reports on the implementation of COBIT processes and quantitatively demonstrated an increased level of ITG, especially in the IT strategic role. A positive relationship amongst ITG maturity and the dissemination of IT-related information was identified, thus improving the level of transparency. Furthermore, the researchers demonstrated that organizations utilize the COBIT framework to govern IT activities for increased performance, visibility, and transparency.

Shaw (2020) conducted a qualitative Delphi study to identify critical success factors (CSFs) in the implementation of ITIL framework. The population target of this study was 12 ITIL experts having more than 10 years' EXP and involved three rounds of interviews. Shaw identified various themes towards successful ITIL implementation consisting of (a) executive sponsorship, (b) senior management commitment, (c) communication, (d) training plans, (e) cost-benefit analysis, and (f) phased approach. The CSFs identified by Shaw (2020) align with the findings by Drew (2019) and Najjar et al. (2020). The need to quantitatively determine the relative importance of each factor towards the adoption of such frameworks is necessary to prioritize initiatives.

Raflesia et al. (2017) investigated the problems related to ITIL adoption. Three different frameworks were used to support the research specifically (a) ITIL, (b) gamification, and (c) user engagement theory and the model was applied on two case studies. Service desk agents are a critical component of ITIL adoption and success, whereby key functions are communication and meetings SLAs. The use of persuasive tools such as the introduction of game elements along service desk adoption positively influenced user engagement and service desk quality. Game elements allow IT leaders to create new challenging workspaces by rewarding team member for every finish task. Similar concept is used in tele sales and call centers. These researchers suggest that gamification can be introduced in DevOps teams to ensure that every task is delivered according to governance structures, whereby abiding members can be rewarded.

Implementation of ITIL in organizations poses different challenges for every organization based on turnover and IT staff. Drew (2019) used the complexity theory to quantitatively investigate such challenges. The population target for this study was 39 respondents in the USA. The bivariate correlation analysis was used to identify a correlation between number of IT staff in an organization and the lack of executive sponsorship, time, financial and human resources. Furthermore, the organizational size (annual turnover), resistance to change, and organizational maturity were statistically significant. The adoption factors affecting ITIL align with adoption of ITG, such as executive support (Riemer et al., 2020) as well as lack of human and financial support (Najjar et al., 2020).

Obwegeser et al. (2019) acknowledged the difficulties in implementing and supporting service management and integrated Lean methodology with ITIL to achieve continuous process improvement. The researchers used the design science research (DSR) approach to construct a framework based on quantitative and qualitative data. This resulted in the development of a framework, which integrated Lean management tools with ITIL’s Continual Service Improvement (CSI). Following a case study implementation, the framework provided a reduction of waste in terms of processes, people, and technology.

The exploration of ITIL adoption in different regions elicited Iden and Eikebrokk (2017) to conduct a survey in the Nordic countries and compare the findings with other cross-national surveys conducted in the UK, US, DACH region and Australia. The researchers demonstrated that organizations in different regions adopted common service management processes, specifically Incident Management (95%), Change Management (88%), Problem Management (71%), and Service Level Management (58%). These results were validated by the findings in Nordic countries.

Enterprise Architecture

Although several frameworks and literature cover ITG processes, a gap between theoretical and practical ITG exists (Smits & van Hillegersberg, 2018). Most research is focused on structures and processes (hard governance); however, behavior and collaboration (soft governance) are equally important. Smits and van Hillegersberg (2018) posited that soft governance may bridge the gap between theoretical and practical ITG and proposed a novel ITG maturity model, which covered hard and soft ITG in exhaustive detail. Several ITG maturity models were identified, including (a) COBIT, (b) MIG, (c) Twelve fields of action, (d) Nine ITG categories, (e) Green IT capability maturity model and (f) COBIT in conjunction with ITIL, TOGAF and other frameworks. The MIG model was identified as the most exhaustive in capturing hard and soft ITG areas. Soft governance areas, which may affect the adoption of ITG, include (a) continuous improvement of the ITG process that ties with the motivation of agile ITG, (b) leadership support, (c) participation, and (d) understanding and trust. These areas were identified and discussed in other studies. Hard governance activities, which are imparted by frameworks, such as COBIT, ITIL and TOGAF include (a) functions and roles, (b) formal collaboration networks, (c) IT decision making, (d) planning, and (e) monitoring.

Misalignment amongst the business and IT, especially with emergence of new IT roles such as DevOps, drove the empirical study conducted by Menglong et al. (2020). Misalignment factors and prevention principles were used to propose a business and IT coevolution (BITC) process, resulting in continuous business-IT alignment. The framework was built using EA structures and coevolutionary analysis. EA can be used as a springboard towards achieving governance amongst development, operations, and business teams.

The identification of EA best practices in large organizations drove the research by Abunadi (2019). The researchers analyzed multiple case studies from 17 organizations that implemented EA business processes to improve analysis, governance, and IT alignment. The study was limited to horizontal practices amongst different business and IT functions. The researcher demonstrated the increased awareness by organizations in adopting EA for ITG to achieve alignment and provide implementation guidance. Iyamu (2018) explored a Zachman implementation in a South African organization. Mapping the various organizational activities with the Zachman framework was critical factor towards a successful implementation of EA. Such framework provided the organization with a foundation for ITG (alignment). Hence, the adoption of EA principles may be used in the implementation of ITG in DevOps environments.

Zhang et al. (2019b) proposed a framework to combine IT resource allocation with EA design process. This model was validated through a case study, whereby the portfolio decision analysis (PDA) method was used to align business functions and applications of system architecture. The model identified cost-efficient applications that support business functions. Furthermore, the researchers acknowledged EA's capability in implementing ITG. Organizations implement ITG to align business functions and applications through a cost-efficient application portfolio. In the case of multiproduct DevOps team, a cost-efficient application portfolio is necessary to govern the technology stack.

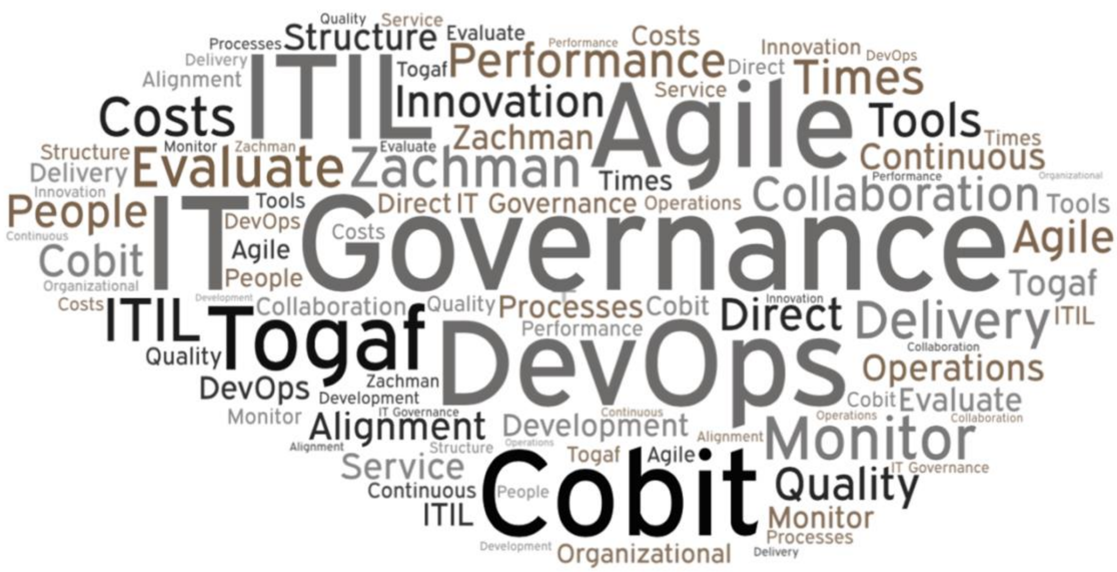
Curyła and Habernal, (2019) compared TOGAF and ZACHMAN frameworks through focused expert groups whereby the criteria for the discussion were based upon implementation, testing, time-consumption, documentation, and schedule planning. The researchers found that the ZACHMAN framework provides an adaptable approach towards the design of corporate architecture because it encapsulates the vision of users, programmers, and designers. Conversely, TOGAF focuses primarily on the business strategy and objectives. Enterprise architecture frameworks such as TOGAF and ZACHMAN are adequate in the design of enterprise solutions. This study shows that continuous delivery is partially covered by ZACHMAN but not by TOGAF.

Transition and Summary

The academic literature relating to technology adoption, ITG, and DevOps research showed that the disciplines overlapped, and that further research was needed to interrelate them. The success of DevOps is based on 4 pillars being culture, automation, measurement, and sharing (Hemon et al., 2020). ITG can formalize innovative practices amongst DevOps teams to ensure that such pillars are managed. The literature review indicated that organizations adopt different frameworks to govern IT teams, including COBIT, ITIL, and EA frameworks. Furthermore, the literature analysis found the UTAUT constructs and moderators in various studies related to the adoption and success of ITG and DevOps. Figure 3 depicts the themes extracted from the literature review.

Figure 3

Word Cloud of Themes



Throughout the literature review, I found that the adoption of ITG has only been quantitatively researched in two studies (Gómez, 2018; Hart & Burke, 2020). Gómez (2018) used TAM and UTAUT theoretical frameworks to understand the relationship between the determinant factors and the BI to use ITG. Gómez found that knowledge related to ITG framework affected the use of ITG. In the UTAUT framework, knowledge is part of the VOL moderator. Hence, a gap in the literature was found related to the factors towards the adoption of ITG for DevOps teams. Fox (2020) and Greene (2020) reviewed ITG adoption for DevOps teams, however these qualitative studies did not analyze the factors that motivate IT leaders towards ITG adoption.

Venkatesh et al. (2003) developed the UTAUT model whereby the BI to adopt technology is dependent on constructs PE, EE, SI, and FC, and moderated by AGE, GND, EXP, and VOL. The use of UTAUT in research, was entirely focused on technology adoption such as continuous delivery (Anderson, 2019), integrated license service information system (Puspitasari et al., 2019), mobile learning (Chao, 2019), and software as a service (Alotaibi, 2016). Hence, this research extended the body of literature by utilizing UTAUT model on a framework rather than a technology. Additionally, this research quantitatively analyzed the relationship between the various factors and the BI to adopt ITG for DevOps teams.

Section 1 introduced the problem statement and the research question, whereby the hypotheses were posited. An extensive literature review pertaining to the research question was presented, whereas the constructs and moderators of the theoretical model were identified in the body of literature. Section 2 comprises the research design and justification, study population and sampling procedure aspects, procedure for analysis, an explanation of threats and ethical concerns, and a summary.

Section 2: The Project

In this section, I reiterated the purpose statement and presented the research method, design, data collection, data analysis technique, reliability, and validity. In the first part I re-examined the purpose of the research and defined the role of the participant. In the second part of this section, I defined the population target and scope and presented an explanation on the adopted data analysis technique. Lastly, I assessed the study's reliability and validity to ensure it meets academic rigor.

Purpose Statement

In this study, I used a quantitative partial least square analysis to understand the factors towards adoption of ITG strategies for multiproduct DevOps teams. The UTAUT model was used as the theoretical framework for this study, whereby the relationship between PE, EE, SI, and FC with BI to adopt ITG was analyzed. I used a validated UTAUT survey instrument to collect the data. The population target for this study was IT leaders who adopted ITG in multiproduct DevOps teams. Hence the population for this study included IT leaders within architecture, development, and operations teams, operating in multiproduct delivery organizations. Global professional LinkedIn groups were used to collect data from the population scope. Hence, this study did not have a specific geographic location whereby the sample is scattered globally. The findings of this research may facilitate IT leaders’ ability to bring about social change by enhancing software delivery, thereby boosting uptime, dependability, and functionality, all of which are essential to end users.

Role of the Researcher

Pragmatism is a philosophical movement enabling researchers to focus on the impact of humans on real-life situations, contexts, or problems (Shalin, 1991). The pragmatic approach details insight on actions, temporality and meaning making (Gross, 2018) on social phenomena. Symbolic interactionism is a sociological movement focused on the continuous social reality changes caused by humans (Shalin, 1991). Although different in nature, the two combined movements retain a common viewpoint on the human's relationship within a particular situation. In this quantitative study, my responsibilities included the design, data collection, analysis, and presentation of findings, in an objective manner. As the study's researcher, I carefully identified, characterized, and evaluated several elements of the study. One of the tenets of quantitative investigation is for the researcher to use participants and established data gathering procedures that allow for replication and generalization of results (House, 2018). However, researching different subjects or context requires customization (Smith, et al., 2020). This signifies that real context-agnostic quantitative research requires the researcher to identify and focus on common items, which can be found in any setting rather than on the specifics. I used the UTAUT instrument for data collection and analysis. Throughout the process I sought to mitigate any personal bias so that data collection is not hampered or skewed. This was achieved by controlling key factors towards biased research, specifically ethics, bias, and validity as defined by Creswell and Creswell (2018). Throughout my 17-year career I have consistently worked with development and operations teams. Over the past 5 years, I have managed DevOps teams in telecommunications, gaming, and fintech industries.

I referred to the *Belmont Report* as an ethical guide to safeguard the participants and ensure that I did not break any protocols. Researchers adhering to the *Belmont Report* have clear guidelines to guarantee that each participant is treated with dignity, kindness, and fairness as defined by Ferdowsian et al. (2020). Prior embarking on this research, I completed a doctoral student researchers' course with CITI to ensure that I was capable to fulfill this role.

Scholars use quantitative research to quantify an issue through statistical analysis (Bloomfield & Fisher, 2019). Furthermore, quantitative studies require validated instruments to ensure reliability of results. For this study, I used the UTAUT model by Venkatesh et al. (2003) as my theoretical framework within this quantitative research. The questions used in the survey were included in Section 1. Factors loading and analysis followed the UTAUT model to ensure reliability of the results.

Researchers use survey protocols to allow other researchers to conduct similar quantitative research using corresponding survey instruments and data collection (Hollin et al., 2019). In this study, I followed a survey protocol to collect data from different LinkedIn groups. I ensured that all respondents were approached, informed, and treated in the same exact way. I submitted an initial post on each LinkedIn group with the following details:

1. Brief overview of ITG

2. Purpose of the study
3. Methodology of the study
4. Requirements to participate in the study
5. Assurance that survey is anonymous
6. Assurance that data will be stored for at least 5 years in anonymous format
7. Assurance that survey will not take longer than 10 minutes
8. Explanation that the results will be shared in the group once study is completed
9. My personal contact details for further clarification
10. Link to SurveyMonkey with consent form and survey questions

Participants

The participants in this study consisted of IT leaders with EXP in adopting ITG for multiproduct DevOps teams. The IT leaders in this quantitative survey were recruited from LinkedIn groups related to ITG, DevOps, COBIT, ITIL, and EA. In the following section, I discuss the demographics and sampling techniques used for the data collection process. I used the UTAUT instrument to collect data related to domain-specific information (ITG) and demographics (AGE, GND, country, industry). Each participant needed to have a leadership position in multiproduct DevOps teams, such as CIOs, Team Leads, IT Managers and DevOps/Software architects. These roles are critical in the adoption and use of ITG.

Research Method and Design

Method

A scientific study has five governing principles, specifically (a) objective, whereby the experiment is free from bias and considers all data; (b) falsifiable, whereby it is possible to demonstrate that a hypothesis is false; (c) reproducible, whereby other researchers can reproduce the same results following the same protocol; (d) predictable, whereby the results can predict future outcome in non-controlled environments; and (e) certifiable, whereby the hypothesis is not accepted until all analysis is conducted (Dykstra, 2016).

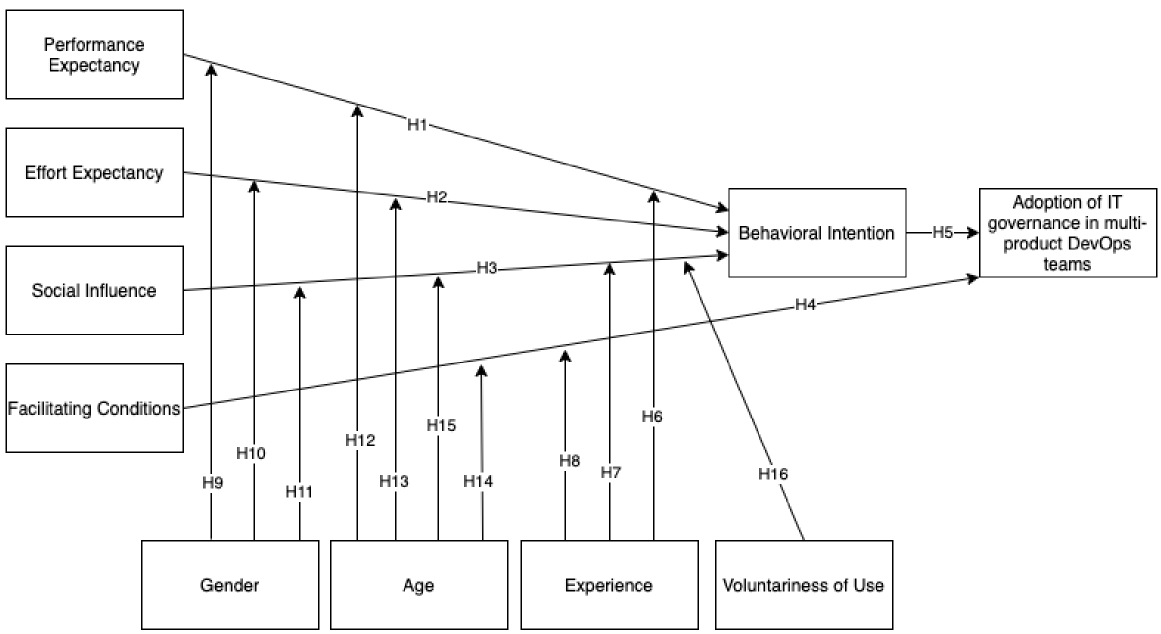
Quantitative research comprises of survey or experimental approaches. In this study, I used a survey methodology to learn more about the factors that influence ITG adoption in multiproduct DevOps teams. An experimental design involves methodically manipulating one or more variables to see how they affect a desired outcome (Creswell & Creswell, 2018). A quasi-experimental design involves the assignment of both experimental and control groups without random assignment (Miller et al., 2020). Both experimental and quasi-experimental research designs were not suitable for my study, due to the availability of subjects and length of the study.

Research Design

For this study, I used the survey design to understand the factors that determine the adoption of ITG for multiproduct DevOps teams. The integrative model provided by Corner (2002) allows researchers to use a generic framework which can be adopted for quantitative research (Haviz & Maris, 2018). Researchers use this framework to adopt different implementations throughout the development of the research, thus enabling them to (a) positively impact the formulation of hypothesis, (b) use of analytical techniques, and (c) data collection methods. My study was based on the natural phenomenon occurring in the workplace whereby IT leaders in multiproduct delivery organizations are not aligned with the relationship between PE, EE, SI, and FC, as moderated by EXP, AGE, GND, VOL, with BI to adopt ITG amongst DevOps teams. I used the modified UTAUT model as shown in figure 4 hereunder.

Figure 4

Modified UTAUT Model



Note. Adapted/Reprinted from "User Acceptance of Information Technology: Toward a Unified View" by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), p. 447. Reprinted with permission.

The first phase of this model was aimed at depicting the hypothesis. This allowed me to determine the constructs and moderators thereby understanding the interaction effect over the dependent variable. In the case of my research problem, five constructs and four moderators were identified. These components were imparted from the UTAUT theoretical concept as shown in Figure 1 (Section 1.14). The second phase of the Corner model (2002) is the formulation of hypotheses. As I adhered to the UTAUT model, I posited 16 hypotheses, which I presented in Section 1.7 (Hypotheses). Previous researchers using the UTAUT model in their studies, discarded certain moderators, however none of them were related to the adoption of ITG. Hence all components of the UTAUT, specifically PE, EE, SI, FC, GND, AGE, VOL, EXP and BI were used in this study. The third phase of the Corner model is focused on the identification of appropriate instrumentation. As part of the UTAUT seminal work, Venkatesh et al. (2003) provided a validated survey to collect data to test the hypotheses. The data analysis is the subject of the fourth phase in the Corner model. In this study, I measured data based on capacity, preparedness, and success through a Likert scale (1 to 5). Hence, the variables were defined as categorical. Chau et al. (2020) used nonlinear analysis to understand the effect of alignment on performance. Nonlinear analysis might help better understand the relationships between the numerous exogenous factors (PE, EE, SI, FC, GND, AGE, VOL, EXP and BI) to adequately predict the adoption and use of ITG. Considering the categorical single dependent variable (adoption of ITG) and categorical independent variables (PE, EE, SI, FC, and BI), the partial least square analysis was deemed the most appropriate for this study.

Population and Sampling

The population for this study was made up of English-speaking IT leaders in software development organizations that have adopted ITG in their DevOps teams. Various LinkedIn groups pertaining to ITG-related frameworks, IT leaders and DevOps practitioners were used to attract the target population for this study. The use of LinkedIn resulted in a randomized sample with geographically scattered participants. Table 4 provides a detailed overview of each LinkedIn group. The members in each group were reached via a post on the group page, as per survey protocol defined in the previous sub-section. On the first page of the survey, the responder had to agree with a consent form before proceeding to the actual questions.

The two general sampling method techniques are probabilistic and non-probabilistic. According to Hasani et al. (2019), non-probabilistic sampling has poor generalizability and is consequently inferior to probability sampling. Furthermore, non-probabilistic sampling is vulnerable to sampling bias since it requires subjective assessment (Lu & Franklin, 2018). For this study, I adopted convenience sampling since I posted my survey on specific LinkedIn groups fitting the population. Adopting such a sampling technique ensured that I provided every participant in the population an equal chance of being selected.

Table 4

LinkedIn Groups

LinkedIn Group	Members	Rational
ITIL COBIT ISO 20000	2,417	ITG practitioners
ISO 20000	3,500	ITG practitioners
The Enterprise Architecture Network (pending approval)	205,322	EA practitioners
TOGAF(R)	20,497	EA practitioners
TOGAF for Architecture	47,976	EA practitioners
The ITIL Group	82,945	ITSM practitioners
ITSM (ITIL) Professionals	140,239	ITSM practitioners
ITIL 4 & ISO20000 Service Management ITSM (pending approval)	177,454	ITG practitioners
COBIT for ITG and Management	3,255	ITG practitioners
Information Technology Audit and Governance Group (pending approval)	87,381	ITG practitioners
Chief Information Officer	250,136	IT leaders
ITG, Risk & Compliance	65,299	ITG practitioners
CDO/CIO/CTO (pending approval)	32,797	IT leaders
DevOps Professionals CI/CD	43,556	DevOps leaders
DevOps Professionals	36,210	DevOps leaders
DevOps | SRE | MLOps | GitOps | CNCF Discussions (pending approval)	73,966	DevOps leaders
DevOps	118,617	DevOps leaders
IT Professionals - Agile Lean Scrum | DevOps | Security | Data | Cloud | SaaS | AI/ML | Automation	300,709	DevOps leaders
COBIT (Official) (new addition)	26,794	ITG practitioners

The total target population covered by all LinkedIn groups was 1,841,830. Utilizing SurveyMonkey's sample size calculator, the recommended target sample was determined at 385, using a confidence level of 95% and margin of error at 5%. This sample size did not factor that IT professionals may be members of different groups (duplicates) and the analytical technique (PLS-SEM); hence a more efficient technique was required. The probability of rejecting a false null hypothesis is defined as the statistical power, which is determined by three factors: (a) the significance level, (b) the effect size, and (c) the sample size (*n*). Because the significance threshold is generally chosen before the research, and the effect size is established by the efficiency of the study, only the sample size may be changed by the researcher (Beck, 2013). By means of an a priori power analysis (Soper, 2022), I determined the target sample size for this at 102. This calculation was based on a one-tailed hypotheses, utilizing anticipated effect size (Cohen's d) at 0.5, desired statistical power level at 0.8 and probability level at 0.05. The sample size of 102 was considered realistic and attainable, considering the timeframe of the project.

However, since this study used the PLS-SEM analysis, a more accurate sample was necessary to address the latent variables PE, EE, SI, FC, BI and adoption (Al-Emran et al., 2020). A SEM sample size calculator was used. The anticipated effect size (*f 2*) was 0.5, desired statistical power level was 0.80, number of latent variables were 6, number of observed variables were 25, and the probability level was 0.05. This resulted in a recommended sample size of 94 participants. Appendix D demonstrates the workings to achieve this sample size.

Ethical Research

A critical element of a doctoral study is to adopt ethics throughout the whole research process. Participants can withdraw from the study in 2 different stages whereby they can either (a) not accept the consent form or (b) not submit the survey as per data collection process depicted in Figure 5. The survey protocol used in this study required the researcher to submit a post in each LinkedIn group with researcher and study details and a link to the survey (SurveyMonkey). The survey did not collect any personal identifiable information (PII), whereby names and emails were not part of the survey. Once the study was completed and approved, the results were submitted to the LinkedIn group through a post. Furthermore, the data collected will be stored for 5 years on (a) an encrypted USB drive and (b) personal Google Drive within an encrypted archive file (.zip format).

To protect study subjects from harm, ethical research involves a set of rules that each researcher must follow. Researchers also have a moral duty to adhere to rules and standards that respect the rights and dignity of each participant through informed consent (Tulyakul & Meepring, 2020), withdrawal from study (Fernandez Lynch, 2020), participant protection (Ross et al., 2018), and confidentiality (Turcotte-Tremblay & Mc Sween-Cadieux, 2018). The element of financial incentivization (Gurzawska et al., 2017) was not considered in this study since participation was not incentivized. Throughout this study, I followed the American Psychological Association's (American Psychological Association, 2017) guidelines as well as the Walden University Institutional Review Board's requirements (IRB). The Walden University IRB oversees reducing the risk that participants may face because of their participation in this study. IRBs examine socio-behavioral research protocols and related material to ensure that participants are safeguarded (Brown et al., 2019). After my proposal was accepted, I went through the IRB process to get permission to conduct the research (IRB, Approval No. 03-03-22-1007390). Because my research involved human beings, the IRB mandated that each participant provide their consent willingly and freely via a written consent form (Tulyakul & Meepring, 2020). Participants were recruited using a LinkedIn Group post that contained the study's goal, qualifying requirements, confidentially information, Walden's IRB contact information, and a link to the SurveyMonkey questionnaire.

Data Collection

Instruments

The instrument used to collect data is based on the original survey questions by Venkatesh et al. (2003). The items used in estimating UTAUT are PE, EE, SI, FC, BI, VOL, GND, AGE and EXP.

Data collection is a critical phase in a doctoral study, whereby the researcher used a method to acquire information on phenomena to answer the research question (Moser & Korstjens, 2017). Psychometric techniques uses theoretical constructs and measuring instruments to quantitatively collect data (Joshi et al., 2015). The purpose of statistical research is to improve survey accuracy by reducing variability both from the researcher, respondent, and the environment (Fienberg & Tanur, 1989). The reliability of the data collection method can be validated through the use of statistical functions such as Cronbach's alpha, split-half correlation, and the Spearman-Brown prediction formula, which were successfully adopted by Anderson (2019). The researcher explored the factors which determine the adoption of ITG in multiproduct DevOps teams. The factors are determined by the theoretical framework used in this study.

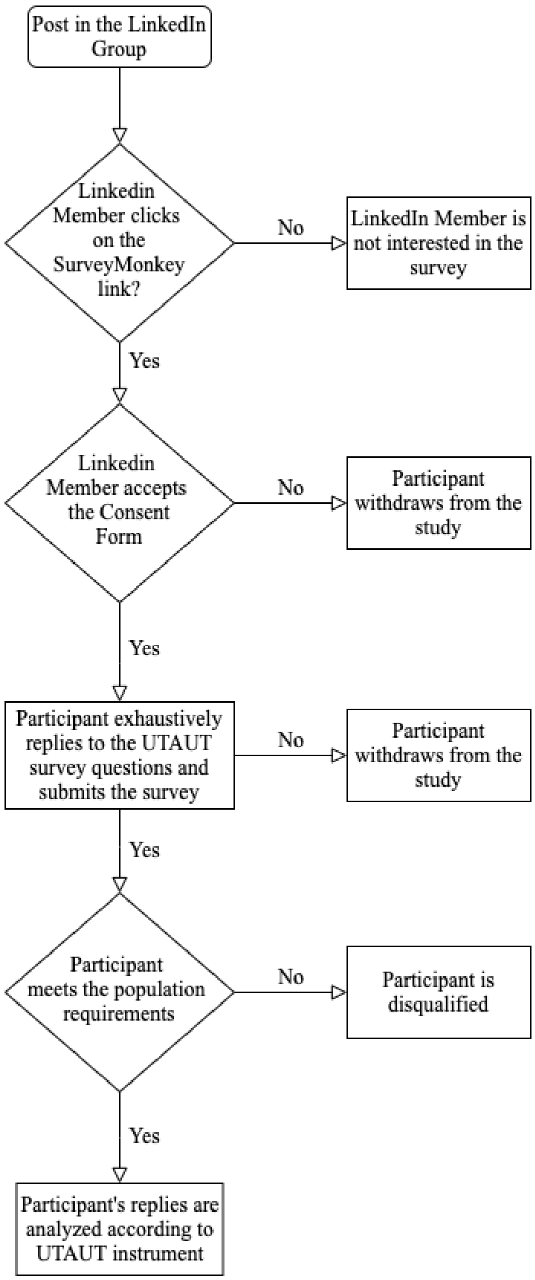
The construction of Likert scale is aimed to provide objective results to an individual's subjectivity (Joshi et al., 2015). Several adaptations of the Likert scale were adopted in the body of research, whereby the researcher needs to determine the adequate number of points on the scale and symmetricity (or asymmetrically) of the scale, thus emphasizing (or not) the notion of neutrality. The survey which was submitted to the population of this study used a 5-point Likert scale ranging from 1 to 5, being Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, and Strongly Agree, respectively. The validity of the Likert scale is driven by the respondents' applicability to the topic and the familiarity of the respondents to the results (Joshi et al., 2015). Louangrath and Sutanapong (2018) identified the 5-point scale as the most robust of the Likert scales. Although results from Likert scales tend to produce ordinal data, a common technique for applying such scale is to sum up several variables to create an interval variable. The reliability of a Likert scale can be measured using the Cronbach alpha, whereas the reliability of 5-point Likert scales can be seen from the various quantitative studies utilizing Likert scales, including the seminal work on UTAUT by Venkatesh et al. (2003).

Data Collection Technique

SurveyMonkey was used to gather data for this research project, as it allows users to create online surveys using a cloud-based platform. Participants completed an electronic survey and supplied informed consent through an electronic form. The initial portion of the survey comprised demographic questions, such as AGE, GND, and EXP, to load the moderators of the research. The participants' thoughts and behavioural intentions toward ITG in multiproduct DevOps teams were the focus of the second portion of the study, which was given using a 5-point Likert scale. Participants in the research were free to leave the survey at any moment and skip any questions they wanted, thus discarding them in the screening process. The data collection process is presented in Figure 5.

Figure 5

Data Collection Process



Data Analysis Technique

My research question was (RQ): What is the relationship between PE, EE, SI, and FC, as moderated by GND, AGE, EXP, and VOL with BI to adopt ITG for multiproduct DevOps teams?

My overarching hypotheses were:

Null Hypothesis 1 ($H_0$1): There is no significant relationship between IT leaders' perceptions of PE, EE, SI, FC, and the BI of IT leaders, as moderated by AGE, GND, EXP, and VOL, to adopt ITG in multiproduct DevOps teams.

Null Hypothesis 1 ($H_0$1): There is a significant relationship between IT leaders' perceptions of PE, EE, SI, FC, and the BI of IT leaders, as moderated by AGE, GND, EXP, and VOL, to adopt ITG in multiproduct DevOps teams.

The nominal scale of measurement is the most basic and simple level of measurement, whereby the researcher assigns a unique numeric value to every different attribute in a variable. This type of variable is descriptive in nature (Suparji et al., 2021) whereby frequency counts can be used to determine the counts per attribute. An Ordinal scale of measurement is applied on variables which can be ordered in a particular manner, such as ascending, descending or on the variable attribute itself. Such a variable provides the researcher further insight than the nominal type, since it is used to categorize research specific attributes (Omilla, 2019). I classified the independent variables (PE, EE, SI, FC, and BI) as ordinal data to represent respondents' views and attitudes since they graded the quantity of participants' perceptions.

Regression Analysis

Researchers use linear regression models to study the correlation among a dependent factor and independent factors (Schmidt & Finan, 2018). The most basic linear regression model involves the study of 2 variables. Bivariate correlation is a statistical approach for determining the link between two variables, whilst bivariate regression analysis is used to identify the effects of two variables on each other (Lee Rodgers & Nicewander, 1988). Both statistical functions are used to determine the pattern (specified as strength and direction) between two variables (Schober et al., 2018), so determining the relationship, with the direction of the correlation and regression being the same, i.e., if the correlation is negative, so is the regression slope. Correlation analysis, through bivariate correlation, is the first step towards causality, since one of the pillars in causality, is the ensuring of a relationship amongst variables. Once a correlation is determined, causality can be determined, through a regression analysis. Whereas the variables are interchangeable in the bivariate correlation, this is not possible in the regression analysis, since the bivariate regression follows a mathematical formula whereby $zy = r\ zx$ (Lee Rodgers & Nicewander, 1988).

However, the values obtained from each technique provide different explanations to the correlation (if any) in place amongst two variables. Bivariate correlation can be analyzed by plotting the variables on an x and y graph, whereby regression can be analyzed using a linear model and determine the distance of the variable plots to the straight line (Trochim et al., 2015). By utilizing this technique, the researcher can determine if there is positive or negative correlation, as well as the pattern of the data through the analysis of the slope in the straight line, hence the regression analysis. This technique can be used for multiple variables through multivariate analysis and regression.

According to Bervell and Umar (2017), there is an apparent exclusion in literature of non-linear relationships of UTAUT exogeneous variables (PE, EE, SI, and FC) in model formation and overall determination of construct predictive relationships. In addition, Chau et al. (2020) made a statistical recommendation for using nonlinear analysis in quantitative research regarding alignment and performance. Additionally, Ramli et al. (2018) conducted a comparative analysis between regression and PLS models, whereby it was found that in terms of discovering mediation effects, PLS-SEM analysis produces fewer contradicting results than regression analysis. This elicited me to investigate an alternative analysis method from regression models.

Structural Equation Modelling

SEM is used if the researcher wants to investigate the causation and effect connection between a collection of independent and dependent variables (Kursunoglu & Onder, 2019). This statistical approach enables the researcher to concurrently evaluate the causation and effect connection of those variables, lowering the influence of Type 1 error (Ramli et al., 2018). Since the UTAUT has various independent variables (PE, EE, SI, FC and BI), the SEM was preferred. Under SEM statistical analysis, there are two prevalent ideas, specifically Covariance based SEM (CB-SEM) and Variance based SEM (VB-SEM) methods (Mohamad et al., 2019). The CB-SEM approach is generally used to validate or reject hypotheses using hypothesis testing (Mikulić & Ryan, 2018). When the sample size is big and the data is roughly regularly distributed, this strategy is useful. Most significantly, the causation and effect connection model must be clearly described (Mia et al., 2019). The second approach in the SEM family, VB-SEM, is more resistant to the premise of normality distribution and sample size, and it is used when the accuracy of the causation and effect connection cannot be guaranteed (Dijkstra & Henseler, 2015). Furthermore, the VB-SEM approach is shown to be best suited for investigating the association between variables (Ali et al., 2018). PLS-SEM is a prediction-oriented method to SEM since it emphasizes on the justification of variances rather than covariances (Shmueli et al., 2016). Therefore, this specific method (PLS-SEM) would explain the variances between the various independent variables (PE, EE, SI, FC and BI) toward the adoption of ITG in multiproduct DevOps teams.

Partial Least Squares

Partial Least Squares (PLS) analysis is a multivariate statistical approach which enables researchers to compare multiple response and explanatory variables. Assuming we have multiple responses defined as $X = TP^T$ and $Y = UQ^T$, PLS will perform regression between T and U by decomposing X and Y keeping each other in account. This results in the formulation of $Y = UQ^T = T\beta Q^T = XP\beta Q^T$. Further analysis will yield the following fact $cov(X^TYQ, X^TYQ) = D'$, where D' "is the eigenvalues of the covariance matrix of X^TY" (Ng, 2013, p. 7). This analytical method is one of a group of covariance-based statistical approaches known as SEM. It was created to cope with multiple regression in situations when there is a limited sample size, missing data, or multicollinearity in the data. It has become increasingly popular in research, where many correlated variables and a limited number of observations pose a significant issue. Both actual data and simulations were used to illustrate partial least squares regression (Garthwaite, 1994). Hair et al. (2019b), recommend using PLS when (a) sample size capabilities are real and when (b) utilizing models with specified constructs. To estimate data from factor model populations, PLS has shown to obtain high levels of statistical power while correcting for Type I errors, albeit at the price of parameter precision (Sarstedt et al., 2016).

Venkatesh et al. (2003) used PLS to examine the reliability and validity of the various constructs (PE, EE, SI, FC, and BI) and moderators (AGE, GDR, VOL, and EXP) loadings. The loadings were used to construct latent variable observations using PLS estimation. To estimate the adjusted R^2, Venkatesh et al. (2003) used the latent variable observations from PLS and examined the data using hierarchical regressions in SPSS to estimate the structural model using ordinary least square (OLS).

Data Cleaning

Part of the data analysis required the identification and elimination of incorrectly structured or duplicated data. Braekman et al. (2018) suggested that online surveys had substantial benefits over earlier data collecting techniques, such as eliminating the omission of items via input-controlled forms, regulating respondents' choices, and giving the researcher better control over survey administration. It was important to employ a drop-down option selection scale so that replies would fall within a reasonable selection range. Web-based Likert scale surveys provide better data collection quality than conventional approaches, which reduces data gathering inconsistencies and data cleaning needs (Buchanan & Scofield, 2018). SurveyMonkey, was used to clean up the information once it was entirely collected. My data gathering procedure nearly eradicated incomplete data by utilizing a logic which required participants to respond each survey question prior going on to the next one. Multiple survey submissions were not allowed by blocking multiple submissions from the same device.

Data Screening

The quality and reliability of data being collected can be improved through a rigorous data screening process, based on theoretical considerations (DeSimone et al., 2014). Johnson et al. (2016) advocated for utilizing a statistical data description and summary to ensure the study's credibility. I conducted a univariate study of data normality, which comprised distribution, central tendency, and variable dispersion descriptive analysis.

Missing Data

According to Koszalinski et al. (2018), raw data must be inspected and confirmed for missing data adjustments and outliers checks before any statistical analysis is performed. Data analysis standards mandate that missing values should be cleaned up and outliers should have their values carefully imputed before moving on to the next step of the study. Data cleansing, according to Kumari and Kennedy (2017), requires thoughtful attention since the outcomes of the statistical analysis depend on it. Using tools such as SPSS, require data cleaning processes to maintain consistency in checks and treating missing replies accurately (Koszalinski et al., 2018). Outliers and other illogical extreme values may be detected using the consistency tests in the missing data cleaning (Koszalinski et al., 2018). To reduce data skewness and ensure data validity, I discarded the survey replies that were incomplete or had missing data in any section.

Assumptions Pertaining to Statistical Analyses

The fundamental assumptions behind SEM are as follows: (a) multivariate, (b) normality, (c) no systematic missing data, (d) a sufficiently high sample size, and (e) accurate model specification (Kaplan, 2001).

Multivariate

The sampling technique is an important consideration for accurate estimation and inference. If there is no specific information indicating the contrary, data is presumed to be created randomly, such as the maximum likelihood estimation approach (Muthén, 1984).

Normality

SEM relies on the assumption that data is drawn from a normally distributed and continuous population (Knights et al., 2020). Because the maximum likelihood estimator is derived directly from the multivariate normal distribution expression, this is especially true for this type of estimation. Maximum likelihood has ideal asymptotic properties if the data are continuous and multivariate normal. This indicates that the estimates are normal, unbiased, and efficient (Kaplan, 2001).

Missing Data

SEM requires complete data for every unit of analysis. For various causes, units may be missing values for one or more of the variables under investigation (Muthén et al., 1987).

Sufficiently Large Sample Size

As a researcher, it might be challenging to determine the right sample size in SEM. There are times when the minimum sample size required for one model is not consistent in terms of (a) attaining acceptable results with the next highest sample size or (b) evaluating the same model with a new seed number (Wolf et al., 2013).

Specification Error

To use SEM, it is necessary that the model be accurately defined. A SEM error is characterized as the removal of important variables from any of its equations. This includes the equations for both the measurement and the structural model. Similarly, missing data, non-normality, and omitted variables affect conclusions thus making the findings incorrect (Kaplan, 2001).

Process for Testing and Assessing the Assumptions

Cain et al. (2017) used univariate and multivariate skewness and kurtosis as measures of nonnormality. These tests were adopted in this study as they are available in SPSS version 27. However, other tests for assessing nonnormality of multivariate data exists. Tenreiro (2017) proposed a novel test for multivariate normality by combining extreme and nonextreme Baringhaus–Henze–Epps–Pulley (BHEP) tests.

Missing data was identified during the screening process in Microsoft Excel. To reduce data manipulation and potential bias, missing answers disqualified the entire questionnaire. The sample size for this study was calculated through a SEM sample size calculator (Soper, 2021). The recommended sample size of 94 participants was achieved by the workings in Appendix D.

The model used in this study involved 25 observed variables loaded from the survey question and 6 latent variables, specifically PE, EE, SI, FC, BI and adoption of ITG.

Actions for Violated Assumptions

Univariate and multivariate skewness and kurtosis test may denote a high deviation from normal distributions, which may reduce the replication of the findings in this study to the population (Liang et al., 2018).

Interpreting Inferential Statistics

An experimental study is objective and considers all the data collected. Hence, the findings can invalidate hypotheses, whilst other researchers may replicate the same results using the same protocol (Dykstra, 2016). The notion of replication is a central theme in the interpretation of inferential statistics (Amrhein et al., 2018). I applied specific statistical metrics, specifically (a) effect sizes, (b) probability values, (c) confidence intervals, and (d) desired statistical power for interpreting my findings (Russ, 2021).

Calculating Effect Size

In a statistical study, the researcher needs to calculate an accurate effect size to identify relationships amongst the variables in sample population (Trochim et al., 2015). Hofmann and Meyer-Nieberg (2018) assert that the effect size is the ideal way for describing how sample findings deviate from the null hypothesis's predictions. The effect size quantifies the predicted outcome's amplitude impact (Marshall & Jonker, 2011). When the data is symmetrically distributed, the effect size is known whereby $d=0.5$ (Botta-Dukát, 2018). However, in case of skewed data, this assumption does not hold. SPSS allows the researcher to assess the normality of the data by means of the Shapiro-Wilk Test, if *Sig.* > 0.05, the data is normally distributed, else the data deviates significantly from normal distribution (Liang et al., 2009). Additionally, a normal quantile-quantile (Q-Q) plot can graphically assist the researcher in observing the dependent variable and its distribution (Kozak & Piepho, 2017).

Calculating Probability Values

In hypothesis testing, a *p*-value helps the researcher decide if the *null* hypothesis has statistical significance. In other words, the statistical significance of a hypothesis gets stronger as the p-value goes down. The alpha value or *p*-value is a core component of statistical analysis providing evidence against the *null* hypothesis, which needs to be calculated to avoid test replication problems (Halsey, 2019). To minimize Type I errors, the alpha value needs to be as low as possible, hence researchers agree to use the arbitrary $p=0.05$. This value is used in my study, whereby the chance of a Type I error is reduced to 5 percent.

Calculating Confidence Intervals

Confidence interval represents the representation of the sample with the population being studied. According to Lee (2016), a confidence interval represents the size of the population by using the mean's point estimate and standard error of the mean. Hofmann and Meyer-Nieberg (2018) denote that conventionally researchers use a 95 percent confidence interval. This means the researcher has 95% confidence that any member in the population falls in the mean of the sample. This conventional value was used in this study whenever applicable.

Desired Statistical Power

The desired statistical power is necessary for the development of SEM. A high-valued statistical power results in over rejection of alternative hypotheses, whereas low-valued statistical power results in null hypotheses not being rejected (McQuitty, 2004). The $\beta = 0.2$ value means that the desired statistical power is set to 0.8 value which is considered a minimal default value both by Soper (2021) as well as Lakens and Albers (2017).

Statistical Software

The data collected in this study was analyzed by means of three software tools, specifically Microsoft Excel, SPSS and SmartPLS. Microsoft Excel is a spreadsheet software which was used for data cleaning purposes. SPSS is a statistical tool developed by IBM Corporation that is extensively used by researchers perform comparison and correlational statistical tests in the context of univariate, bivariate, and multivariate analysis using both parametric and non-parametric statistical approaches. SmartPLS is a statistical program which provides SEM analysis utilizing Ordinary Least Square estimation approaches (Ong & Puteh, 2017). These three tools were used in this research to identify the factors affecting IT leaders in the adoption of ITG in multiproduct DevOps teams.

Reliability and Validity

Reliability

The instrument's reliability refers to how well it functions and produces consistent results (Bell et al., 2020). Test-retest, internal consistency, and inter-observer reliability are three ways of determining the reliability of an instrument. (Okita et al., 2020).

The UTAUT instrumentation uses a questionnaire to obtain the independent variables within the UTAUT model. The questions and constructs within the questionnaire are adopted from prior research in technology adoption. The reliability of the UTAUT constructs (PE, EE, SI, FC and BI) is validated through the Cronbach's alpha, whereby $\alpha>0.75$ denotes good reliability and $\alpha>0.90$ results in excellent reliability (Vidal-Alaball et al., 2020). Preliminary validation of the UTAUT instrumentation was conducted by Venkatesh et al. (2003) on 215 respondents (N=215), whereby an examination on the highest loading items "*suggested that they adequately represented the conceptual* *underpinnings of the constructs*" (Venkatesh et al., 2003, p. 457). Further validation of the UTAUT model, was conducted using cross validation, whereby data gathered from an additional organization (N=133) confirmed the preliminary results, and the validity of the constructs and results, thus limiting the variation caused by the change of items. The reliability of the data collection method can be validated through the use of statistical functions such as Cronbach's alpha, split-half correlation, and the Spearman-Brown prediction formula, which were successfully adopted by Anderson (2019).

The test-retest reliability method is used to determine a measure's consistency across time. Internal consistency reliability is a term used to describe the consistency of a test's outcomes across items. The degree to which various observers produce consistent assessments of the same phenomena is measured using inter-observer dependability. Reliability is more closely associated with a metric that produces consistent outcomes. Validity is aided by reliability, albeit the latter is not a condition that guarantees validity (Knekta et al., 2019). The degree to which the two separate measurements were associated was determined by using the correlation coefficient calculation to determine reliability (Afthanorhan et al., 2020). The test-retest reliability method was used to determine the consistency of a measure across time. The results of the test performed to determining the correlation coefficient for two sets of data should be between 0 and 1, with a value over 0.8 being acceptable (Jhangiani et al., 2019). Participant mistakes, researcher errors, researcher bias, and participant bias are some of the sources of reliability errors (Cooper &

Schindler, 2012). Through a series of cross-validation tests the UTAUT survey was confirmed to be trustworthy and valid.

PLS-SEM reported and assessed indicator reliability, reflecting modeling, internal consistency, and discriminant reliability. Additionally, bootstrapping was used to determine the importance of the outer loadings of the indicator (Wong, 2013). Instead of utilizing Cronbach's Alpha, the PLS-SEM analysis may be performed to estimate the distinct outer loadings of the indicators using composite reliability (Wong, 2013). Internal consistency reliability was used to evaluate the consistency of the test outcomes across items. In this study, internal consistency reliability was used to concentrate on respondent's replies across all survey questions (Preece et al., 2018). The participants' ratings on linked items must be associated and represent the same construct value. The split-halves test is one method to internal consistency, which is popular because of its simplicity and involves breaking the data included in each construct into two pieces.

Following the completion of the test, the score for each of the sections is calculated in order to investigate the link between the two components. A consistency value of more than 0.8 is deemed appropriate, whereas the expectation for a factor loading must be 0.7, and the cross-loadings must be at least 0.3. (Jhangiani et al., 2019). Reflective modeling is the only way to achieve internal consistency. The collinearity of the formative model is decided by the structural model's evaluation. If the findings reveal a variable inflation factor (VIF) of more than 5, there is a collinearity issue (Russo & Stol, 2021).

Validity

Lather (1993, p. 697) defines the concept of validity in research as “multiple, partial, endlessly deferred”. The purpose of statistical research is to improve survey accuracy by reducing variability (Fienberg & Tanur, 1989) both from the researcher, respondent, and the environment. The validity of quantitative data is based on the reliability concern. The main characteristic of reliability is consistency (Leung, 2015), whereby every respondent needs to be presented with the same survey and analysed using the same analysis technique. Another key aspect of data validity in quantitative research, is the removal of bias both from the researcher, respondent, and environment. Such bias can be overcome through confirmability (Cope, 2014), whereby the knowledge derived from interviews and analysis are confirmed by the respondents thus eliminating researcher bias. Participant bias can be analyzed through cross-examinations and personal judgements (Norris, 1997). Internal validity relates to a research's internal findings and whether or not the effects identified in a study are attributable to independent variable manipulation (Hauser et al., 2018). The degree to which the research findings may be extrapolated outside the limits of the sample group is known as external validity (Sarstedt et al., 2017).

Construct and content validity are also examined while evaluating the PLS model's validity. The term "content validity" was used to describe the degree to which the measures accurately reflected the underlying notions (Hair et al., 2019a). Because all of the questions in the survey were modified from cited research, the model employed for this investigation showed good content validity (Venkatesh et al., 2003). The degree to which instrument measurements represent latent constructs that are not usually seen is referred to as construct validity (Kyle et al., 2020). The indicators, which were meant to provoke a reaction relating to a construct, did not directly observe the constructs in the research (Venkatesh et al., 2003). The PLS-SEM proved to be the most effective method for finding unobservable and difficult-to-measure latent variables, making the PLS model excellent for enterprises (Sarstedt et al., 2022). The latent variables were tested for redundancy using convergent validity (Cheah et al., 2018). If the correlation or path coefficients between the latent variables were 0.80 or higher after the redundancy analysis, convergent validity was believed to be established (Zhang et al., 2019a). For composite dependability, a factor loading value of greater than 0.5 is considered appropriate (Purwanto & Sudargini, 2021). It is considered a positive indication if it is equal to or greater than 0.7.

If the indicators are strongly correlated, the collinearity of indicators is used to resolve concerns of collinearity (Hair et al., 2019a). The VIF which was obtained by a multiple regression test, was determined using the SmartPLS multiple regression test, and the tolerance values were used to investigate collinearity (Russo & Stol, 2021). Multicollinearity was indicated if the full research produced a VIF score more than 10. A VIF larger than 5 suggests a collinearity problem (Russo & Stol, 2021).

Transition and Summary

The purpose of this research is to learn more about the motives for establishing ITG in multiproduct DevOps teams. This section provided information on the research protocol, target population, sample size, data processing technique, and tests to establish reliability and validity of the results. The participants in this research were IT leaders with prior EXP in adopting ITG for multiproduct DevOps teams. The IT professionals that participated in this quantitative survey were recruited via LinkedIn groups that included ITG, DevOps, COBIT, ITIL, and Enterprise Architecture. According to the calculations, the entire target population was 1,841,830 people, and the sample size required to create an appropriate SEM was 94 people.

PLS-SEM gives the researcher the ability to simultaneously evaluate and analyze all constructs as per the UTAUT framework (Ramli et al., 2018). Latent variables are constructed using a version of principal component analysis using PLS-SEM (Cheah et al., 2020). The validity and reliability of constructs are tested using reflective models. The direction of the latent variables is reflected in the measuring variables (survey questions) used to identify them (Muthén, 2001). Reflective measurement modeling makes extensive use of indicators and latent variables that are interconnected and interchangeable (Thaker et al., 2020). The latent variables must be normalized before using PLS-SEM to make sure the model works correctly. The variables are automatically normalized by partial least squares software, whereby the mean and standard deviation of each variable must be equal to one (1). The latent variables' values are determined by linear combinations of the indicator variables, which must be normalized (Garson, 2016). Structural pathway coefficients range from zero (0) to plus or minus one (1), with the strongest paths being those that are closest to absolute one (1).

The reliability aspect of the study is confirmed by means of Test-retest, internal consistency, and inter-observer reliability. The validity aspect of the study was confirmed by construct and content testing on the latent variables and their collinearity. A factor loading value greater than 0.5 is considered acceptable for composite reliability (Purwanto & Sudargini, 2021). The SmartPLS multiple regression test was used in this research to calculate the VIF. The tolerance values were used to analyse collinearity in the results of the multiple regression test (Russo & Stol, 2021). If the results of the research showed a VIF value more than 10, it was determined that multicollinearity had occurred, whereby a VIF greater than 5 indicates the presence of a collinearity issue (Russo & Stol, 2021).

Section 3 presents the findings for the research question through (a) descriptive statistics, (b) hypotheses confirmation or disconfirmation and (c) theoretical framework confirmation or disconfirmation. Furthermore, this section evaluates the potential uses of my findings in future studies and its social impact.

Section 3: Application for Professional Practice and Implications for Change

In this section, the findings of this study were presented and applied to the professional practice. Thereafter, the implications for social change stemming from these findings were discussed. Additionally, in this section, I provided recommendations based on the findings, towards the adoption of ITG in multiproduct DevOps teams. Furthermore, this section presented recommendations for future study on ITG adoption within this study's context. Lastly, a personal reflection and final conclusions on this research were presented to the reader.

Overview of Study

The purpose of this quantitative partial least squares analysis study was to determine the relationship between BI to adopt ITG strategies for multiproduct DevOps teams and PE, EE, SI, and FC, as moderated by EXP, GND, AGE, and VOL.

The population sample feedback (n=205) was judged trustworthy (α=0.935). The UTAUT model went through three revisions throughout the data analysis phase to ensure that all relevant correlations were detected and appropriately described within the scope of the research. SPSS was used for initial data validation and exploratory factor analysis (EFA). A partial least squares analysis determined which criteria are relevant in the BI to adopt ITG.

To such end, I used SmartPLS to examine the models. SmartPLS also guaranteed confirmatory factor analysis (CFA) as well as internal reliability and consistency. Through the analysis, I discovered a positive correlation amongst PE and SI towards BI of DevOps executives to implement ITG. Furthermore, I discovered that FC has a positive correlation with ITG adoption and use. DevOps and ITG experience (EXP) positively moderate SI towards the BI to adopt ITG.

Upon further investigation, I discovered that ITG use (USE) positively influences DevOps maturity, whereas ITG maturity is positively related to the effort to use ITG. Furthermore, ITG is positively related to DevOps maturity, and DevOps maturity is indirectly related to the BI to adopt ITG.

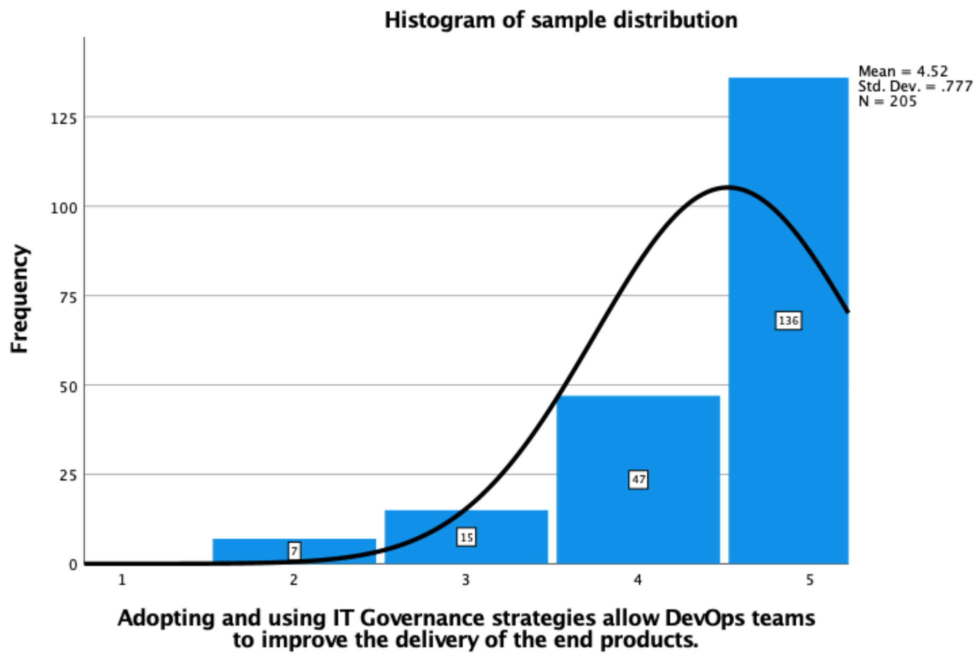
Presentation of the Findings

The data collection process was approved by IRB on the 3rd of March 2022. The survey was deployed on the 5th of March 2022 and closed on 25th March 2022. The survey collected a total of 489 respondents. The respondents who qualified for the study were filtered by the initial 3 questions in the survey. These questions ensured that the participants are IT leaders, aged over 18 years, managing DevOps teams in a multiproduct environment through an ITG framework. Upon filtering on these qualifying questions, the total number of actual respondents reduced to 266, thus denoting a 55% completion rate.

After reviewing the data in MS Excel, respondents who did not fully answer the survey were excluded. This resulted in a final population of 205 respondents (*n=205*). The distribution sample is shown in Figure 6, hereunder.

Figure 6

Histogram of Sample Distribution



Demographics, Firmographics and ITG Use

After the initial data cleansing in MS Excel, I used SPSS (version 28) to (a) understand the population and (b) conduct testing related to normality and reliability. I evaluated the data uploaded to SPSS for missing data both in the constructs for UTAUT and demographics as per Table 5.

Table 5

Demographics

No.	Frequency	Male or Female	AGE	DevOps EXP	ITG certification	ITG use
N	Valid	205	205	205	205	205
	Missing	0	0	0	0	0

The demographics analysis revealed a GND disparity whereby the majority of the participants were male (95.6%). GND disparity is also apparent in the population of the United States, with women filling just 25% of technical positions in the country (Richter, 2021). A further confirmation of this discrepancy was conducted through a visual review of the population in the LinkedIn groups defined in Table 6 whereby a high majority of DevOps leaders are men.

Table 6

Gender Statistics

Frequency	Sex	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	9	4.4	4.4	4.4
	Male	196	95.6	95.6	100
	Total	205	100.0	100.0	

The sample consisted of two age groups, whereby most IT leaders are in the 31–40 age range (71.7%) and the remaining 28.3% falls in the 41–50 age range, as per Table 7. These findings align with demographics results by Atlassian (2020).

Table 7

Age Statistics

Frequency	Sex	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	31-40	147	71.7	71.7	71.7
	41-50	58	28.3	28.3	100
	Total	205	100.0	100.0	

The firmographics pertaining to the organizations' size and revenue are presented in Tables 8 and 9. These results align with the findings presented by Atlassian (2020) whereby DevOps and ITG are mostly used in high-revenue and large organizations.

Table 8

Organization Size Statistics

Frequency	Organization size	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 100 employees	29	14.1	14.1	14.1
	101-250 employees	10	4.9	4.9	19.0
	251-500 employees	72	35.1	35.1	54.1
	501-1000 employees	6	2.9	2.9	57.0
	Over 1001 employees	88	42.9	42.9	100
	Total	205	100.0	100.0	

Table 9

Revenue Statistics

Frequency	Organization size	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than $1 million	2	1.0	1.0	1.0
	$1 million - $5 million	2	1.0	1.0	2.0
	$5 million - $10 million	1	0.5	0.5	2.5
	$10 million - $20 million	4	2.0	2.0	4.5
	Over $20 million	196	95.6	95.6	100
	Total	205	100.0	100.0	

Table 10 demonstrates an interesting divergence from normal ITG adoption, whereby DevOps teams do not use traditional ITG frameworks such as COBIT. Most of the IT leaders used an ad-hoc framework (78.5%), potentially consisting of multiple or adapted frameworks to govern DevOps team, whereas ITIL is the second most used ITG framework (18%).

Table 10

ITG Use Statistics

Frequency	Organization size	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	COBIT	0	0.0	0.0	0.0
	ITIL	37	18.0	18.0	18.0
	Enterprise architecture	0	0.0	0.0	18.0
	ISO27000 /ISO27001/ ISO38500	2	1.0	1.0	19.0
	SCRUM	4	2.0	2.0	21.0
	KANBAN	1	0.5	0.5	21.5
	Combination of above or ad-hoc	161	78.5	78.5	100
	Total	205	100.0	100.0	

Moreover, 82% of the respondents claim that their organization mandates ITG, as per Table 11. This finding can have various interpretations; however, it is evident that organizations value the coordination of DevOps teams with the rest of the organization. This is validated by the positive correlations of external SI and organization's PE towards BI to adopt and use of ITG, as identified in Iteration 3 (Tables 28 and 29). A DevOps culture is characterized by open communication, clear roles and responsibilities, respect, and trust, all of which are important success elements (Masombuka, 2020).

Table 11

Mandatory ITG adoption Statistics

Frequency	It is mandatory for my organization to have an ITG body?	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	168	82.0	82.0	82.0
	No	37	18.0	18.0	100
	Total	205	100.0	100.0	

Initial Reliability Analysis

Following an understanding of the sample population, testing was necessary to ensure that all constructs were reliable both holistically and by latent variable (PE, EE, SI, FC, BI, and USE). During the initial analysis I identified a high degree of reliability in Cronbach's alpha and McDonald's omega (α=.935 and Ω=.924), based on the 25 questions in the survey, as per Table 12.

Table 12

Initial SPSS Reliability Statistics

Cronbach's alpha	McDonald's omega	N of items
.935	.924	25

However, a deeper understanding of the normality amongst the constructs was necessary. Following a Skewness and Kurtosis analysis, it was determined that not all indicators met normality when tested together. This was further confirmed through the

Shapiro-Wilk test. Further normality analysis including non-parametric correlation analysis demonstrated that the sample was statistically significant at 0.01 rather than 0.05. The normality tests are shown in Appendix E. Following the validation of normality amongst constructs, descriptive statistics test was conducted to identify the reliability should any of the constructs was deleted, as per Table 13.

Table 13

SPSS Standardized Construct Reliability Statistics

Construct	Initial Cronbach alpha	Initial N of items		Cronbach's alpha based on standardized items	Final N of items
PE	.819	6	→	.819	6
EE	.677	4	→	.804	3
SI	.539	4	→	.741	3
FC	.893	4	→	.893	4
BI	.833	3	→	.833	3
Use	.655	4	→	.986	2

Following this analysis, the initial number of constructs (25) was reduced to 21, to ensure reliability amongst the constructs for each latent variable. The reliability analysis on the 21 constructs is shown in Table 14. Both the Cronbach alpha and McDonald's omega improved thus legitimizing the modification to the model.

Table 14

SPSS Standardized SPSS Reliability Statistics

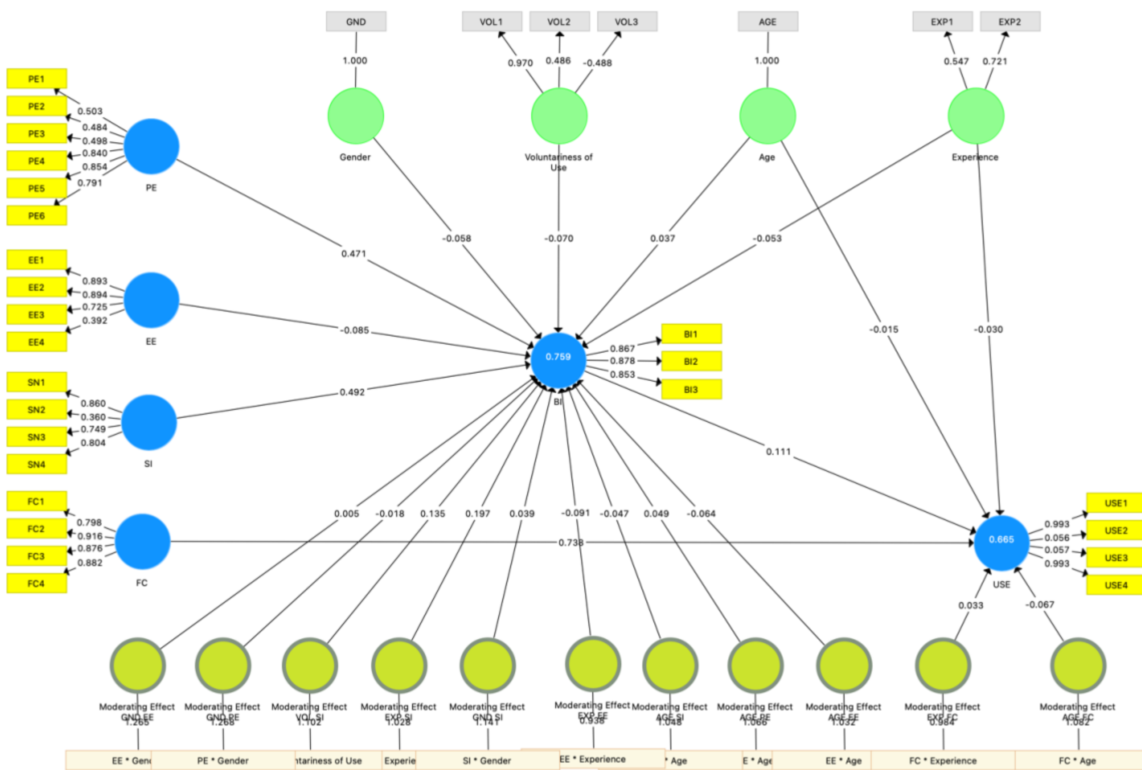
Cronbach's alpha	McDonald's omega	N of items
.940	.935	21

Iteration 1 – UTAUT PLS-SEM Model

After understanding and confirming the normality and reliability in SPSS, the sample was uploaded to SmartPLS in the UTAUT model. Figure 7 shows all the constructs initially proposed in the UTAUT model as presented by Venkatesh et al. (2003).

Figure 7

PLS-SEM Model Using all Variables



Upon analysis, various outliers were identified both in the constructs and the moderators. These were identified by (a) low Cronbach alpha and average variance extracted (AVE) as, per Table 15 and (b) high inner VIF values, as per Table 16.

Table 15

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AGE	1.000	1.000	1.000	1.000
BI	0.833	0.833	0.900	0.750
EE	0.727	0.855	0.830	0.569
EXP	-0.456	-0.462	0.577	0.410
FC	0.892	0.908	0.925	0.755
GND	1.000	1.000	1.000	1.000
Moderating Effect AGE EE	1.000	1.000	1.000	1.000
Moderating Effect AGE FC	1.000	1.000	1.000	1.000
Moderating Effect AGE PE	1.000	1.000	1.000	1.000
Moderating Effect AGE SI	1.000	1.000	1.000	1.000
Moderating Effect EXP EE	1.000	1.000	1.000	1.000
Moderating Effect EXP FC	1.000	1.000	1.000	1.000
Moderating Effect EXP SI	1.000	1.000	1.000	1.000
Moderating Effect GND EE	1.000	1.000	1.000	1.000
Moderating Effect GND PE	1.000	1.000	1.000	1.000
Moderating Effect GND SI	1.000	1.000	1.000	1.000
Moderating Effect VOL SI	1.000	1.000	1.000	1.000
PE	0.818	0.981	0.831	0.466
SI	0.667	0.761	0.800	0.519
USE	0.652	0.992	0.686	0.495
VOL	0.107	1.199	0.371	0.471

Table 16

Inner VIF Values

	BI	USE
AGE	1.655	1.011
BI		1.655
EE	7.165	
EXP	1.399	1.045
FC		1.671
GND	2.015	
Moderating Effect AGE EE	10.480	
Moderating Effect AGE FC		1.041
Moderating Effect AGE PE	10.948	
Moderating Effect AGE SI	2.426	
Moderating Effect EXP EE	1.513	
Moderating Effect EXP FC		1.075
Moderating Effect EXP SI	1.754	
Moderating Effect GND EE	16.159	
Moderating Effect GND PE	31.139	
Moderating Effect GND SI	15.099	
Moderating Effect VOL SI	2.638	
PE	8.691	
SI	2.331	
USE		
VOL	1.919	

The resulting model was considerably different than the one determined in SPSS, since the reliable model consisted of 18 constructs. Due to this high divergence from the proposed 25 constructs, a new calculation for sample size was conducted as per Figure 17 in Appendix D. The recommended sample size was determined as 200 and therefore the sample size (*n=205*) was adequate for the study.

Due to reliability and internal VIF concerns the EE (EE) latent variable consisted of one construct, specifically *EE4* which measures the question "*Learning to adopt and participate in an ITG framework is easy*". When using covariance-based SEM, single-item variables may create identification and convergence issues; however, this is not a problem when using PLS-SEM (Garson, 2016; Hair et al., 2014). Furthermore, following initial reliability analysis, the GND moderator was also removed. The constructs pertaining to EXP were split into separate constructs due to reliability, thus having DevOps EXP and ITG EXP. The full list of constructs removed to achieve a reliable model are:

- *PE5* – Adopting and using ITG strategies increase the alignment of DevOps teams with other business departments.
- *EE1* – Adopting and using ITG strategies increase the alignment of DevOps teams with other business departments.
- *EE2* – My interaction with other stakeholders in the adoption and participation of ITG is clear and understandable.
- *EE3* – I currently find it easy to adopt and participate in an ITG framework.

- *SN2* – DevOps engineers think that I should adopt and participate in an ITG framework.
- *USE2* – I spend a lot of time modifying the structure of the ITG framework currently used in my organization.
- *USE3* – I spend a lot of time modifying the structure of the ITG framework currently used in my organization.

Iteration 2 – UTAUT PLS-SEM Model

The reliable UTAUT model is shown in Figure 8, whereas the revised construct reliability, validity and internal VIFs are show in Tables 17 and 18.

Figure 8

Revised PLS-SEM Model

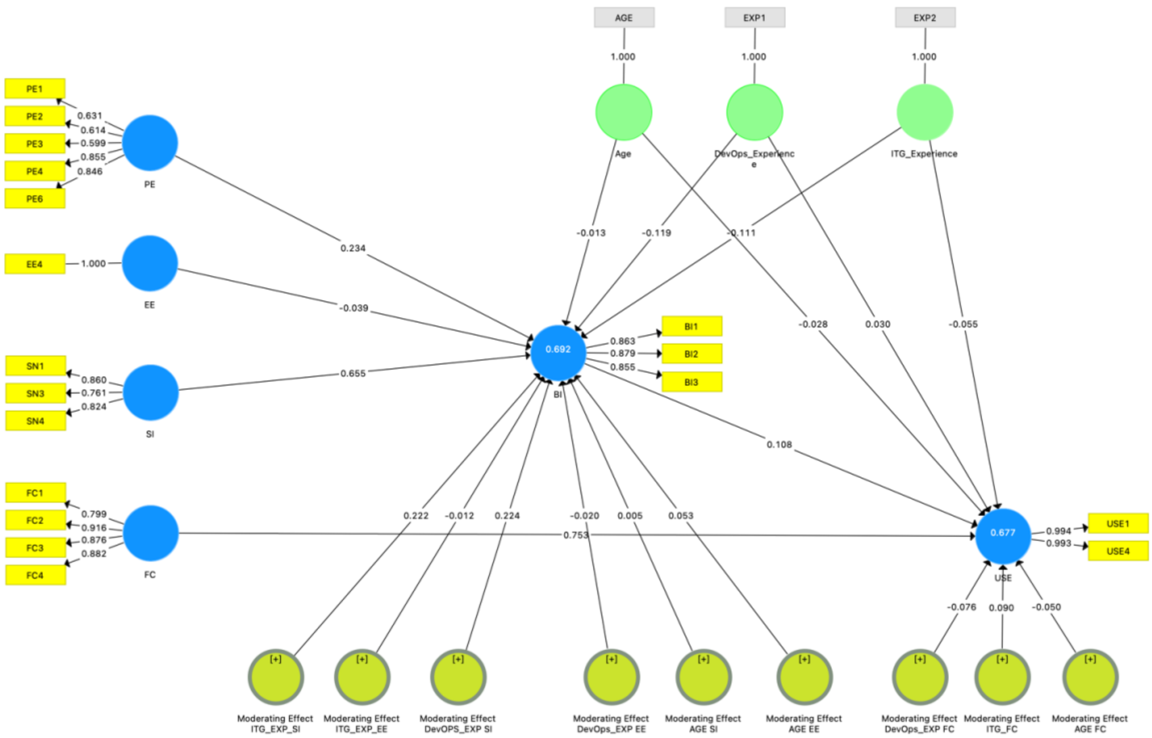


Table 17

Revised Construct Reliability and Validity Analysis

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AGE	1.000	1.000	1.000	1.000
BI	0.833	0.833	0.900	0.750
DevOps_EXP	1.000	1.000	1.000	1.000
EE	1.000	1.000	1.000	1.000
FC	0.892	0.908	0.925	0.755
ITG_EXP	1.000	1.000	1.000	1.000
Moderating Effect AGE EE	1.000	1.000	1.000	1.000
Moderating Effect AGE FC	1.000	1.000	1.000	1.000
Moderating Effect AGE SI	1.000	1.000	1.000	1.000
Moderating Effect DevOPS_EXP SI	1.000	1.000	1.000	1.000
Moderating Effect DevOps_EXP EE	1.000	1.000	1.000	1.000
Moderating Effect DevOps_EXP FC	1.000	1.000	1.000	1.000
Moderating Effect ITG_EXP_EE	1.000	1.000	1.000	1.000
Moderating Effect ITG_EXP_SI	1.000	1.000	1.000	1.000
Moderating Effect ITG_FC	1.000	1.000	1.000	1.000
PE	0.814	0.897	0.839	0.516
SI	0.751	0.772	0.856	0.666
USE	0.986	0.991	0.993	0.986

Table 18

Revised Inner VIF Values

	BI	USE
AGE	1.107	1.081
BI		1.660
DevOps_EXP	1.147	1.152
EE	1.473	
FC		1.693
ITG_EXP	1.144	1.101
Moderating Effect AGE EE	1.124	
Moderating Effect AGE FC		1.080
Moderating Effect AGE SI	1.174	
Moderating Effect DevOPS_EXP SI	1.186	
Moderating Effect DevOps_EXP EE	1.108	
Moderating Effect DevOps_EXP FC		1.149
Moderating Effect ITG_EXP_EE	1.127	
Moderating Effect ITG_EXP_SI	1.095	
Moderating Effect ITG_FC		1.050
PE	1.748	
SI	1.251	
USE		

After confirming the reliability of the revised model, bootstrapping was conducted, using 5,000 subsamples and a significance level of 0.01 as obtained from the nonparametric correlations analysis conducted in SPSS as per Table 37 in Appendix E. The settings for the bootstrapping exercise are shown in Figures 9 and 10.

Figure 9

Bootstrapping Setting of Revised Model

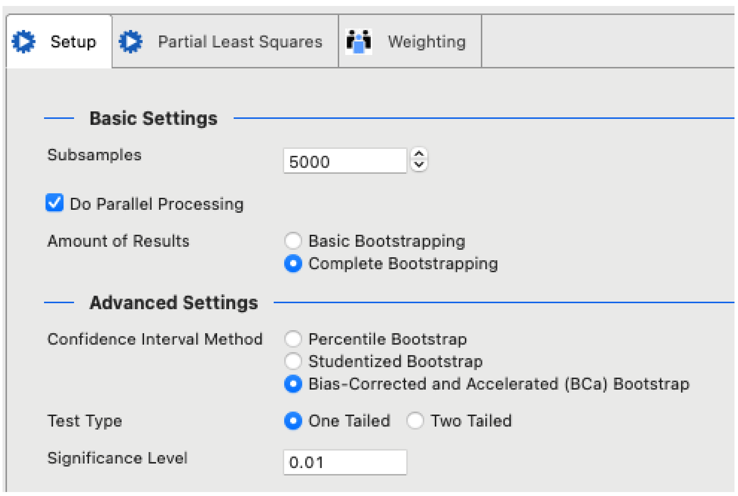
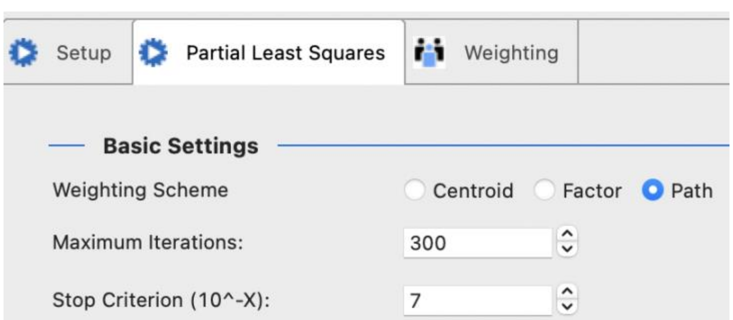


Figure 10

PLS-SEM Path Weighting Scheme



The bootstrapping results obtained from this test are presented in Figure 11 and were used to validate the hypotheses posited in Section 1, through path coefficients as per Table 19.

Figure 11

Bootstrapped Reliable UTAUT Model

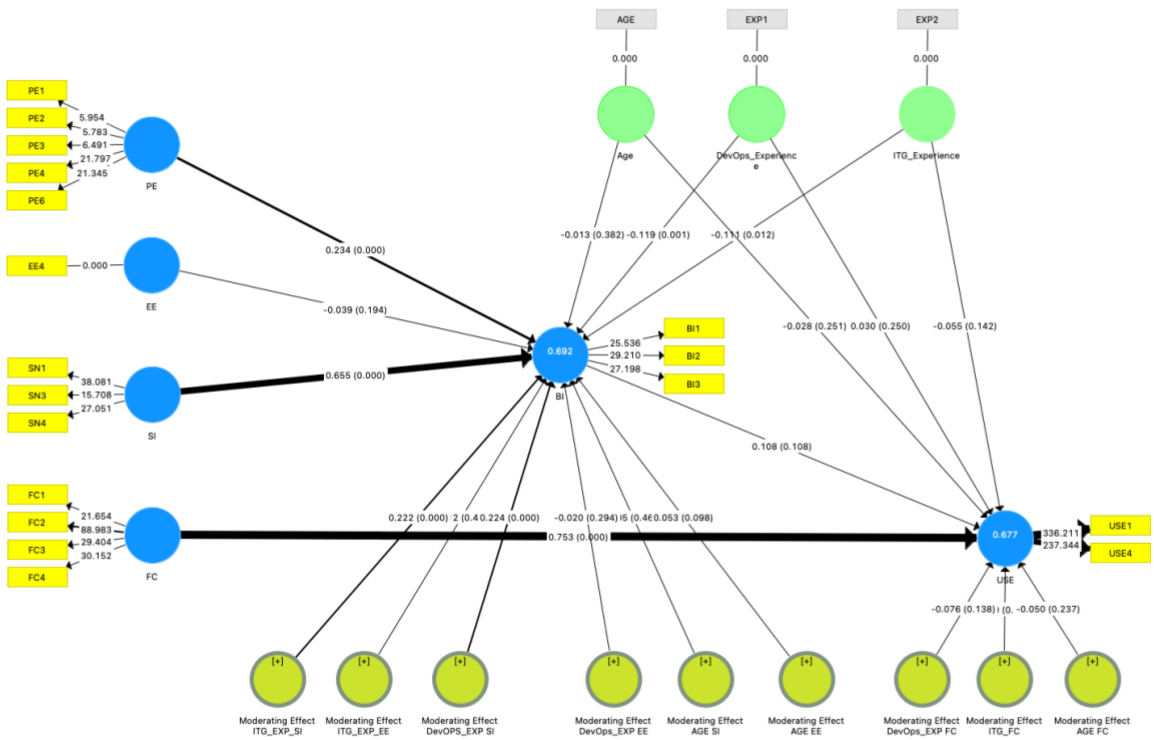


Table 19

Path Coefficients for Reliable UTAUT Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
FC -> USE	0.753	0.762	0.072	10.423	0.000
SI -> BI	0.655	0.656	0.045	14.426	0.000
Moderating Effect ITG_EXP_SI -> BI	0.222	0.215	0.052	4.303	0.000
Moderating Effect DevOPS_EXP SI -> BI	0.224	0.217	0.054	4.138	0.000
PE -> BI	0.234	0.236	0.065	3.568	0.000
DevOps_EXP -> BI	-0.119	-0.115	0.04	2.931	0.002
ITG_EXP -> BI	-0.111	-0.108	0.050	2.251	0.012
Moderating Effect AGE EE -> BI	0.053	0.054	0.042	1.28	0.100
BI -> USE	0.108	0.107	0.086	1.257	0.104
Moderating Effect ITG_FC -> USE	0.090	0.084	0.079	1.148	0.126
Moderating Effect DevOps_EXP FC -> USE	-0.076	-0.081	0.070	1.087	0.139
ITG_EXP -> USE	-0.055	-0.050	0.052	1.052	0.146
EE -> BI	-0.039	-0.038	0.045	0.872	0.192
Moderating Effect AGE FC -> USE	-0.050	-0.041	0.069	0.721	0.236
AGE -> USE	-0.028	-0.031	0.041	0.677	0.249
DevOps_EXP -> USE	0.030	0.034	0.046	0.664	0.253
Moderating Effect DevOps_EXP EE -> BI	-0.020	-0.022	0.035	0.559	0.288
AGE -> BI	-0.013	-0.015	0.041	0.311	0.378
Moderating Effect ITG_EXP_EE -> BI	-0.012	-0.015	0.052	0.224	0.411
Moderating Effect AGE SI -> BI	0.005	0.008	0.047	0.103	0.459

The reliability of the results was also validated through the AVE analysis, as per Table 20.

Table 20

AVE of Reliable UTAUT Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	P Values
AGE	1.000	1.000	0.000	
BI	0.750	0.749	0.038	0.000
DevOps_EXP	1.000	1.000	0.000	
EE	1.000	1.000	0.000	
FC	0.755	0.754	0.03	0.000
ITG_EXP	1.000	1.000	0.000	
Moderating Effect AGE EE	1.000	1.000	0.000	
Moderating Effect AGE FC	1.000	1.000	0.000	
Moderating Effect AGE SI	1.000	1.000	0.000	
Moderating Effect DevOPS_EXP SI	1.000	1.000	0.000	
Moderating Effect DevOps_EXP EE	1.000	1.000	0.000	
Moderating Effect DevOps_EXP FC	1.000	1.000	0.000	
Moderating Effect ITG_EXP_EE	1.000	1.000	0.000	
Moderating Effect ITG_EXP_SI	1.000	1.000	0.000	
Moderating Effect ITG_FC	1.000	1.000	0.000	
PE	0.516	0.513	0.050	0.000
SI	0.666	0.666	0.032	0.000
USE	0.986	0.986	0.007	0.000

I used the Heterotrait-Monotrait (HTMT) ratios and identified certain latent variables were similar, since they exceed 0.85. The similarities were found in FC → BI, SI → BI, PE → EE, PE → FC, and FC → USE, as per Table 21.

Table 21

Heterotrait-Monotrait (HTMT) Ratios

	BI	DevOps EXP	EE	FC	ITG EXP	PE	SI
DevOps EXP	0.227						
EE	0.405	0.194					
FC	0.869	0.303	0.434				
ITG EXP	0.253	0.286	0.254	0.248			
PE	0.670	0.251	0.880	0.890	0.263		
SI	1.036	0.355	0.386	0.679	0.270	0.603	
USE	0.800	0.273	0.418	0.921	0.243	0.799	0.653

The R Square results for both BI ($R^2 = 0.673$) and USE ($R^2 = 0.664$) were greater than 0.10, as per Table 22, thus denoting that the constructs are adequate in explaining the variance.

Table 22

R Square

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BI	0.673	0.698	0.039	17.098	0.000
USE	0.664	0.691	0.050	13.167	0.000

The results from the reliable UTAUT model ensured the statistical significance of the following hypotheses:

Alternative Hypothesis 1 (H_a1): PE is positively related to the BI to adopt ITG.

Alternative Hypothesis 3 (H_a3): SI is positively related to the BI to adopt ITG.

Alternative Hypothesis 4 (H_a5): FC are positively related to the use of ITG.

Alternative Hypothesis 7 (H_a7): DevOps EXP has a positive moderating effect between SI and BI to adopt ITG

Alternative Hypothesis 7 (H_a7): ITG EXP has a positive moderating effect between SI and BI to adopt ITG

The model identified PE and SI as key factors towards the BI to adopt ITG, whilst FC effect the use of ITG. Furthermore, EXP, defined as DevOps EXP and ITG EXP, is a significant moderator in the relation between SI and BI to adopt ITG. However, the model did not correlate BI and USE variables. The lack of exhaustive correlations may be attributed to the fact that UTAUT is normally used on technology rather than procedural frameworks. Whereas technology is normally associated with positive traits, operational frameworks might induce both positive and negative factors and motivated by organizational maturity.

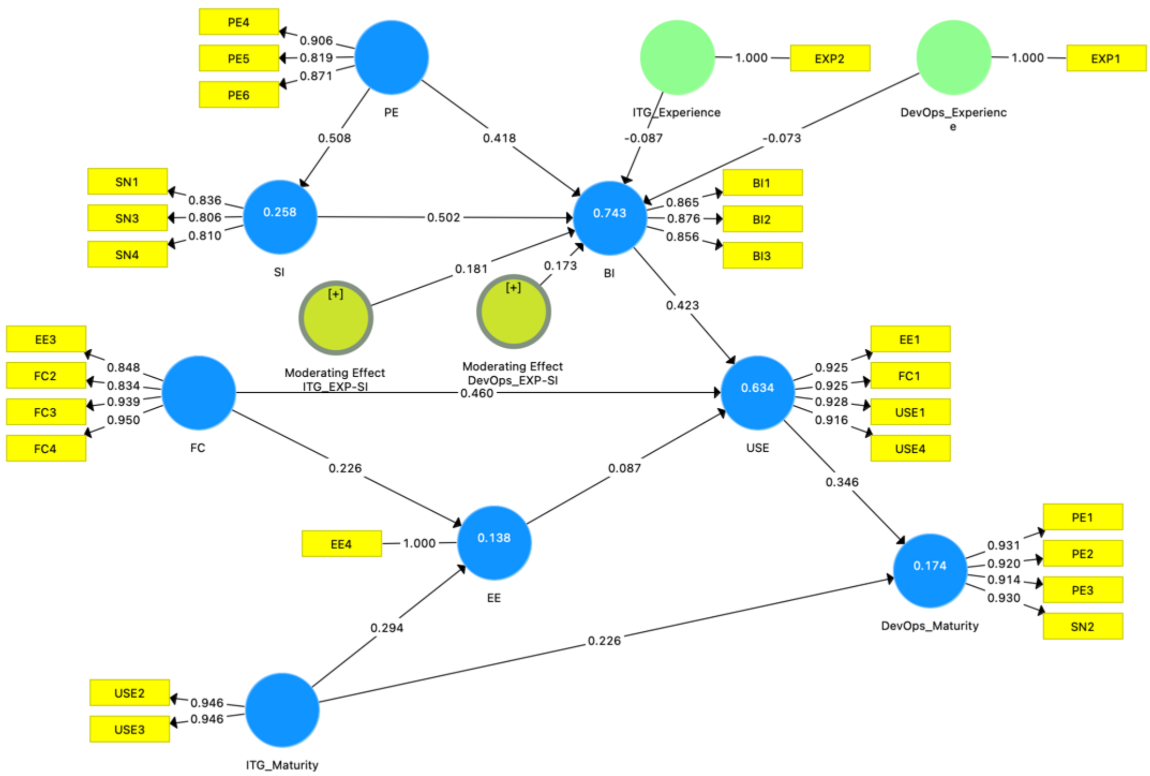
Iteration 3 – UTAUT PLS-SEM model

The lack of conclusive correlational results elicited me to continue investigating the UTAUT constructs and indicators to develop a revised UTAUT model, specifically for this problem. Such model is based on the foundations of the original UTAUT results and extends on the notions of DevOps and ITG maturity to further understand the correlations between the various constructs.

To this end, I conducted an EFA on SPSS to further understand the correlations amongst the various constructs. The results of this analysis are shown in Appendix F, whereby construct *EE2* was found to cause negative relationship with the rest of the constructs. The statement in *EE2* construct was "*My interaction with other stakeholders in the adoption and participation of ITG is clear and understandable*". After removing the EE2 factor, by means of EFA, I identified five components which resulted in five latent variables. To retain the same format of the UTAUT framework, the proposed model included eight latent variables with different constructs and configurations. The proposed model is shown in Figure 12 whereas the constructs configuration is shown in Table 23.

Figure 12

Proposed Model to Understand Adoption and Use Factors of ITG



FC reflects the facilitating condition to adopt and use an ITG framework determined by indicators *EE3*, *FC2*, *FC3*, and *FC4*. *PE* reflects the expected performance gains of adopting ITG from an organizational perspective and is composed of *PE4*, *PE5*, and *PE6*. *SI* is composed by social norms indicators *SN1*, *SI3*, and SN4, which determines the organizational support toward the adoption and use of ITG. The *EE4* indicator determines the effort to use ITG. This indicator is not associated to the *BI* variable, since in the original, UTAUT model it was found that EE is not significant towards the adoption of ITG. *BI* is retained in its entirety as per the UTAUT model (*BI1*, *BI2* and *BI3*). *Use* of ITG is composed by of a combination of constructs from EE and FC in conjunction with original UTAUT model, specifically *EE1*, *FC1*, *USE1*, and *USE4*. DevOps maturity (*DevOps_Maturity*) is composed on internal performance indicators (*PE1*, *PE2*, *PE3*), and DevOps engineers need to adopt and use ITG (*SN2*). ITG maturity (*ITG_Maturity*) is composed of indicators denoting the stability and changes during the use of ITG amongst DevOps teams (*USE2* and *USE3*).

Table 23

Constructs of Modified UTAUT Model for ITG Adoption and Use

Latent Variable	Constructs
PE	*PE4*: Adopting and using ITG strategies increase the alignment of DevOps teams with other IT teams.
	PE5: Adopting and using ITG strategies increase the alignment of DevOps teams with other business departments.
	PE6: Adopting and using ITG strategies allow DevOps teams to improve the delivery of the end products.
SI	*SI1*: People in my organization, who influence my behavior, think that I should adopt and participate in an ITG framework.
	SI3: The senior management of my organization was helpful in adopting an ITG framework.
	SI4: In general, the organization supports the adoption and value of ITG.
FC	*EE3*: I currently find it easy to adopt and participate in an ITG framework.
	FC2: I have the necessary knowledge to adopt and collaborate in an ITG framework.
	FC3: Specialized training is available to assist me in adopting and collaborating in an ITG framework.
	FC4: A specific person (or group) is available for assistance when I face difficulties in the adoption and participation of an ITG framework.
BI	*BI1*: I intend to adopt and participate in an ITG framework in the next 12 months.
	BI2: I predict I would adopt and participate in an ITG framework in the next 12 months.
	BI3: I plan to adopt and participate in an ITG framework in the next 12 months.
USE	*EE1*: My role in the adoption and participation of an ITG framework is clear and understandable.
	FC1: I have the necessary resources to adopt and collaborate in an ITG framework.
	USE1: Participating in an ITG framework is a core responsibility of my role in my organization
	USE4: I consistently participate in an ITG framework.
EE	*EE4*: Learning to adopt and participate in an ITG framework is easy.
DevOps_Maturity	*PE1*: I find the adoption and use of ITG strategies useful to manage DevOps teams.
	PE2: Adopting and using ITG strategies enable DevOps teams to accomplish tasks more quickly.
	PE3: Adopting and using ITG strategies increase the productivity of DevOps teams.
	SI2: DevOps engineers think that I should adopt and participate in an ITG framework.
ITG_Maturity	*USE2*: I spend a lot of time modifying the structure of the ITG framework currently used in my organization.
	USE3: I participated in different ITG frameworks within my organization.

This modified UTAUT model posited additional hypotheses extended from the ones in Section 1, whereby:

Alternative Hypothesis 17 (H_a17): Organizational PE to adopting and using ITG, is positively related to SI from external key members in the organization.

Alternative Hypothesis 18 (H_a18): FC in using ITG is positively related to the effort of using ITG.

Alternative Hypothesis 19 (H_a19): Effort of using ITG, is positively related to the actual use of ITG.

Alternative Hypothesis 20 (H_a20): Use of ITG is positively related to DevOps maturity.

Alternative Hypothesis 21 (H_a21): ITG maturity is positively related to the effort to use ITG

Alternative Hypothesis 22 (H_a22): ITG is positively related to DevOps maturity

Alternative Hypothesis 23 (H_a23): Indirectly, BI to adopt ITG is positively related to improving DevOps maturity

A CFA was conducted on SmartPLS, as per Figure 13 to ensure that the Outer loadings (Table 24) and AVE (Table 25) are correct.

Figure 13

Confirmatory Factor Analysis (CFA) for Proposed Model

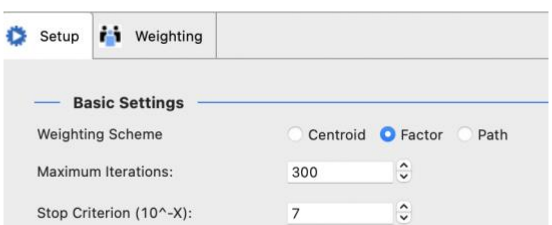


Table 24

Outer Loadings for CFA

	BI	DevOps Maturity	EE	FC	ITG Maturity	DevOps EXP-SI	ITGEXP-SI	PE	SI	USE
BI1	0.865									
BI2	0.876									
BI3	0.856									
EE1										0.925
EE3				0.848						
EE4			1.000							
EXP1										
EXP2										
FC1										0.925
FC2				0.834						
FC3				0.939						
FC4				0.950						
PE1		0.931								
PE2		0.920								
PE3		0.914								
PE4								0.906		
PE5								0.819		
PE6								0.871		
SI * DevOps EXP						1.000				
SI * ITG EXP							0.996			
SN1									0.836	
SN2		0.930								
SN3									0.806	
SN4									0.810	
USE1										0.928
USE2					0.946					
USE3					0.946					
USE4										0.916

Table 25

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	0.833	0.833	0.900	0.75
DevOps_EXP	1.000	1.000	1.000	1.000
DevOps_Maturity	0.943	0.943	0.959	0.853
EE	1.000	1.000	1.000	1.000
FC	0.915	0.915	0.941	0.8
ITG_EXP	1.000	1.000	1.000	1.000
ITG_Maturity	0.884	0.884	0.945	0.896
Moderating Effect DevOps_EXP-SI	1.000	1.000	1.000	1.000
Moderating Effect ITG_EXP-SI	1.000	1.000	1.000	1.000
PE	0.832	0.832	0.900	0.750
SI	0.751	0.751	0.858	0.668
USE	0.942	0.942	0.959	0.853

Furthermore, the model passed the SRMR fitness test at the 99% confidence interval as per Table 26.

Table 26

SRMR Model Fitness

	Original Sample (O)	Sample Mean (M)	95%	99%
Saturated Model	0.086	0.039	0.045	0.049
Estimated Model	0.121	0.05	0.062	0.067

Following the confirmation that the model is reliable, bootstrapping was applied as per Iteration 2 and results are shown in Figure 14 and Tables 27, 28, 29, 30, 31, and 32.

Figure 14

Proposed Bootstrapped UTAUT Model

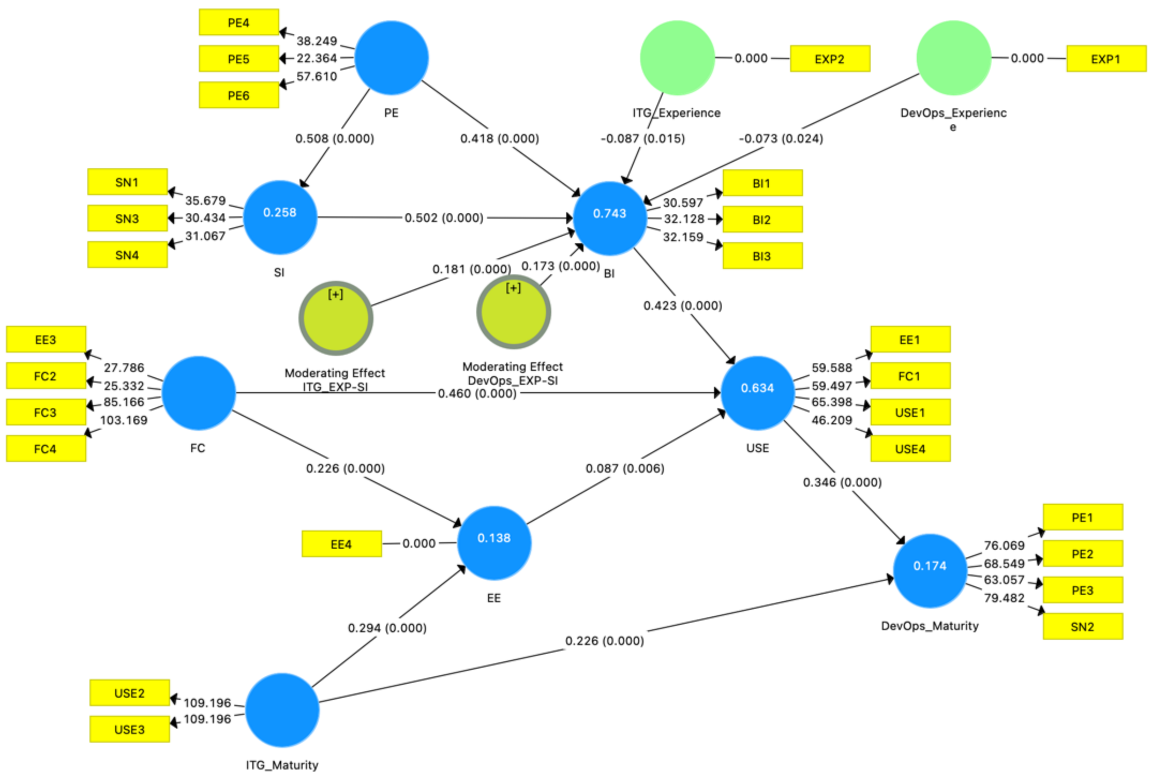


Table 27

R Square for Proposed Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BI	0.743	0.751	0.033	22.274	0.000
DevOps_Maturity	0.174	0.178	0.039	4.494	0.000
EE	0.138	0.142	0.032	4.273	0.000
SI	0.258	0.261	0.054	4.748	0.000
USE	0.634	0.64	0.063	10.127	0.000

Table 28

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PE -> SI	0.508	0.508	0.053	9.499	0.000
SI -> BI	0.502	0.504	0.055	9.207	0.000
USE -> DevOps_Maturity	0.346	0.346	0.050	6.882	0.000
PE -> BI	0.418	0.416	0.061	6.827	0.000
FC -> USE	0.460	0.460	0.074	6.215	0.000
ITG_Maturity -> EE	0.294	0.291	0.050	5.822	0.000
BI -> USE	0.423	0.423	0.076	5.541	0.000
ITG_Maturity -> DevOps_Maturity	0.226	0.223	0.052	4.308	0.000
Moderating Effect ITG_EXP-SI -> BI	0.181	0.179	0.045	4.023	0.000
FC -> EE	0.226	0.226	0.057	3.984	0.000
Moderating Effect DevOps_EXP-SI -> BI	0.173	0.172	0.046	3.787	0.000
EE -> USE	0.087	0.086	0.035	2.515	0.006
ITG_EXP -> BI	-0.087	-0.088	0.040	2.185	0.014
DevOps_EXP -> BI	-0.073	-0.072	0.036	2.021	0.022

Table 29

Total Indirect Effects

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PE -> BI	0.255	0.255	0.034	7.535	0.000
SI -> USE	0.212	0.212	0.041	5.198	0.000
PE -> USE	0.285	0.285	0.058	4.931	0.000
BI -> DevOps_Maturity	0.146	0.146	0.032	4.623	0.000
FC -> DevOps_Maturity	0.166	0.167	0.038	4.363	0.000
SI -> DevOps_Maturity	0.073	0.073	0.017	4.313	0.000
PE -> DevOps_Maturity	0.098	0.098	0.023	4.302	0.000
Moderating Effect ITG_EXP-SI -> USE	0.076	0.076	0.025	3.066	0.001
Moderating Effect DevOps_EXP-SI -> USE	0.073	0.073	0.024	3.051	0.001
Moderating Effect ITG_EXP-SI -> DevOps_Maturity	0.026	0.026	0.009	2.852	0.002
Moderating Effect DevOps_EXP-SI -> DevOps_Maturity	0.025	0.025	0.009	2.821	0.002
ITG_Maturity -> USE	0.026	0.025	0.011	2.424	0.008
ITG_Maturity -> DevOps_Maturity	0.009	0.009	0.004	2.155	0.016
FC -> USE	0.020	0.019	0.009	2.146	0.016
EE -> DevOps_Maturity	0.030	0.030	0.014	2.099	0.018
ITG_EXP -> USE	-0.037	-0.038	0.019	1.901	0.029
ITG_EXP -> DevOps_Maturity	-0.013	-0.013	0.007	1.849	0.032
DevOps_EXP -> USE	-0.031	-0.031	0.017	1.838	0.033
DevOps_EXP -> DevOps_Maturity	-0.011	-0.011	0.006	1.809	0.035

Table 30

Specific Indirect Effects

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PE -> SI -> BI	0.255	0.255	0.034	7.535	0.000
SI -> BI -> USE	0.212	0.212	0.041	5.198	0.000
BI -> USE -> DevOps_Maturity	0.146	0.146	0.032	4.623	0.000
FC -> USE -> DevOps_Maturity	0.159	0.160	0.036	4.404	0.000
PE -> SI -> BI -> USE	0.108	0.108	0.025	4.369	0.000
SI -> BI -> USE -> DevOps_Maturity	0.073	0.073	0.017	4.313	0.000
PE -> BI -> USE	0.177	0.176	0.043	4.103	0.000
PE -> SI -> BI -> USE -> DevOps_Maturity	0.037	0.037	0.01	3.826	0.000
PE -> BI -> USE -> DevOps_Maturity	0.061	0.061	0.016	3.770	0.000
Moderating Effect ITG_EXP-SI -> BI -> USE	0.076	0.076	0.025	3.066	0.001
Moderating Effect DevOps_EXP-SI -> BI -> USE	0.073	0.073	0.024	3.051	0.001
Moderating Effect ITG_EXP-SI -> BI -> USE -> DevOps_Maturity	0.026	0.026	0.009	2.852	0.002
Moderating Effect DevOps_EXP-SI -> BI -> USE -> DevOps_Maturity	0.025	0.025	0.009	2.821	0.002
ITG_Maturity -> EE -> USE	0.026	0.025	0.011	2.424	0.008
ITG_Maturity -> EE -> USE -> DevOps_Maturity	0.009	0.009	0.004	2.155	0.016
FC -> EE -> USE	0.020	0.019	0.009	2.146	0.016
EE -> USE -> DevOps_Maturity	0.03	0.03	0.014	2.099	0.018
ITG_EXP -> BI -> USE	-0.037	-0.038	0.019	1.901	0.029
ITG_EXP -> BI -> USE -> DevOps_Maturity	-0.013	-0.013	0.007	1.849	0.032
DevOps_EXP -> BI -> USE	-0.031	-0.031	0.017	1.838	0.033
DevOps_EXP -> BI -> USE -> DevOps_Maturity	-0.011	-0.011	0.006	1.809	0.035
FC -> EE -> USE -> DevOps_Maturity	0.007	0.007	0.004	1.688	0.046

Table 31

HTMT Ratios

	Original Sample (O)	Sample Mean (M)	1%	99%
DevOps_EXP -> BI	0.077	0.100	0.020	0.216
DevOps_Maturity -> BI	0.243	0.243	0.089	0.395
DevOps_Maturity -> DevOps_EXP	0.011	0.062	0.009	0.182
EE -> BI	0.240	0.239	0.079	0.390
EE -> DevOps_EXP	0.007	0.056	0.001	0.178
EE -> DevOps_Maturity	0.883	0.884	0.831	0.928
FC -> BI	0.595	0.595	0.398	0.783
FC -> DevOps_EXP	0.125	0.129	0.023	0.267
FC -> DevOps_Maturity	0.291	0.291	0.141	0.445
FC -> EE	0.237	0.237	0.088	0.387
ITG_EXP -> BI	0.113	0.120	0.021	0.250
ITG_EXP -> DevOps_EXP	0.186	0.184	0.077	0.282
ITG_EXP -> DevOps_Maturity	0.100	0.109	0.024	0.243
ITG_EXP -> EE	0.092	0.096	0.002	0.239
ITG_EXP -> FC	0.064	0.089	0.025	0.225
ITG_Maturity -> BI	0.014	0.084	0.022	0.216
ITG_Maturity -> DevOps_EXP	0.032	0.066	0.006	0.202
ITG_Maturity -> DevOps_Maturity	0.256	0.256	0.137	0.389
ITG_Maturity -> EE	0.313	0.311	0.182	0.434
ITG_Maturity -> FC	0.084	0.107	0.047	0.215
ITG_Maturity -> ITG_EXP	0.153	0.154	0.015	0.325
Moderating Effect DevOps_EXP-SI -> BI	0.218	0.218	0.047	0.379

Table 31 (continued)

	Original Sample (O)	Sample Mean (M)	1%	99%
Moderating Effect DevOps_EXP-SI -> DevOps_EXP	0.082	0.099	0.002	0.293
Moderating Effect DevOps_EXP-SI -> DevOps_Maturity	0.032	0.068	0.010	0.185
Moderating Effect DevOps_EXP-SI -> EE	0.039	0.060	0.001	0.184
Moderating Effect DevOps_EXP-SI -> FC	0.124	0.130	0.022	0.291
Moderating Effect DevOps_EXP-SI -> ITG_EXP	0.056	0.062	0.001	0.177
Moderating Effect DevOps_EXP-SI -> ITG_Maturity	0.016	0.061	0.005	0.191
Moderating Effect ITG_EXP-SI -> BI	0.241	0.241	0.096	0.368
Moderating Effect ITG_EXP-SI -> DevOps_EXP	0.056	0.062	0.001	0.171
Moderating Effect ITG_EXP-SI -> DevOps_Maturity	0.077	0.087	0.012	0.218
Moderating Effect ITG_EXP-SI -> EE	0.063	0.074	0.001	0.207
Moderating Effect ITG_EXP-SI -> FC	0.059	0.088	0.019	0.237
Moderating Effect ITG_EXP-SI -> ITG_EXP	0.068	0.095	0.002	0.293
Moderating Effect ITG_EXP-SI -> ITG_Maturity	0.036	0.073	0.006	0.226
Moderating Effect ITG_EXP-SI -> Moderating Effect DevOps_EXP-SI	0.115	0.116	0.004	0.259
PE -> BI	0.885	0.886	0.797	0.969
PE -> DevOps_EXP	0.144	0.147	0.023	0.286
PE -> DevOps_Maturity	0.353	0.354	0.195	0.507
PE -> EE	0.301	0.302	0.144	0.459

Table 31 (continued)

	Original Sample (O)	Sample Mean (M)	1%	99%
PE -> FC	1.041	1.042	1.007	1.086
PE -> ITG_EXP	0.085	0.103	0.021	0.239
PE -> ITG_Maturity	0.057	0.096	0.030	0.230
PE -> Moderating Effect DevOps_EXP-SI	0.168	0.172	0.044	0.318
PE -> Moderating Effect ITG_EXP-SI	0.126	0.152	0.069	0.273
SI -> BI	0.874	0.878	0.738	1.033
SI -> DevOps_EXP	0.151	0.16	0.033	0.337
SI -> DevOps_Maturity	0.224	0.227	0.072	0.409
SI -> EE	0.200	0.206	0.063	0.377
SI -> FC	0.407	0.410	0.219	0.607
SI -> ITG_EXP	0.068	0.102	0.020	0.250
SI -> ITG_Maturity	0.097	0.127	0.043	0.253
SI -> Moderating Effect DevOps_EXP-SI	0.066	0.085	0.011	0.236
SI -> Moderating Effect ITG_EXP-SI	0.022	0.067	0.011	0.192
SI -> PE	0.643	0.645	0.498	0.796
USE -> BI	0.768	0.769	0.611	0.892
USE -> DevOps_EXP	0.138	0.141	0.022	0.271
USE -> DevOps_Maturity	0.372	0.371	0.230	0.501
USE -> EE	0.292	0.292	0.152	0.423
USE -> FC	0.753	0.753	0.613	0.876
USE -> ITG_EXP	0.147	0.147	0.026	0.270
USE -> ITG_Maturity	0.024	0.076	0.016	0.198
USE -> Moderating Effect DevOps_EXP-SI	0.174	0.175	0.041	0.305
USE -> Moderating Effect ITG_EXP-SI	0.183	0.184	0.072	0.299
USE -> PE	0.962	0.963	0.888	1.032
USE -> SI	0.528	0.530	0.365	0.685

Table 32

Statistical Significance of Constructs in Modified UTAUT Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
EE -> DevOps_Maturity	0.858	0.857	0.022	39.786	0.000
PE -> BI	0.737	0.736	0.044	16.766	0.000
PE -> FC	0.908	0.908	0.013	71.537	0.000
SI -> BI	0.691	0.692	0.042	16.426	0.000
SI -> PE	0.508	0.509	0.054	9.359	0.000
USE -> BI	0.680	0.679	0.055	12.345	0.000
USE -> FC	0.699	0.699	0.054	12.846	0.000
USE -> PE	0.851	0.852	0.034	25.211	0.000
USE -> SI	0.444	0.444	0.058	7.690	0.000
FC -> BI	0.519	0.518	0.073	7.093	0.000
USE -> DevOps_Maturity	0.351	0.350	0.056	6.245	0.000
ITG_Maturity -> EE	0.294	0.294	0.048	6.150	0.000
PE -> DevOps_Maturity	0.313	0.313	0.060	5.249	0.000
USE -> EE	0.284	0.283	0.056	5.032	0.000
SI -> FC	0.338	0.339	0.071	4.740	0.000
ITG_Maturity -> DevOps_Maturity	0.233	0.232	0.052	4.507	0.000
PE -> EE	0.274	0.273	0.061	4.502	0.000
FC -> DevOps_Maturity	0.270	0.270	0.062	4.352	0.000
ITG_EXP -> DevOps_EXP	-0.186	-0.185	0.043	4.345	0.000
Moderating Effect ITG_EXP-SI -> BI	0.220	0.220	0.053	4.145	0.000
FC -> EE	0.227	0.226	0.062	3.641	0.000
USE -> Moderating Effect ITG_EXP-SI	0.178	0.178	0.049	3.631	0.000
DevOps_Maturity -> BI	0.215	0.213	0.062	3.486	0.000
EE -> BI	0.219	0.216	0.064	3.441	0.000
USE -> Moderating Effect DevOps_EXP-SI	0.169	0.168	0.057	2.962	0.002
Moderating Effect DevOps_EXP-SI -> BI	0.199	0.198	0.068	2.930	0.002
SI -> DevOps_Maturity	0.188	0.187	0.067	2.812	0.002
SI -> EE	0.173	0.172	0.067	2.591	0.005
PE -> Moderating Effect DevOps_EXP-SI	0.154	0.153	0.06	2.548	0.005
USE -> ITG_EXP	-0.142	-0.143	0.057	2.479	0.007

Final results from analysis

Following the final analysis, the full list of validated hypotheses is shown hereunder:

Alternative Hypothesis 1 (H_a1): PE is positively related to the BI to adopt ITG.

Alternative Hypothesis 3 (H_a3): SI is positively related to the BI to adopt ITG.

Alternative Hypothesis 4 (H_a4): FC are positively related to the use of ITG.

Alternative Hypothesis 7 (H_a7): DevOps EXP has a positive moderating effect between SI and BI to adopt ITG

Alternative Hypothesis 7 (H_a7): ITG EXP has a positive moderating effect between SI and BI to adopt ITG

Alternative Hypothesis 17 (H_a17): Organizational PE to adopting and using ITG, is positively related to SI from external key members in the organization.

Alternative Hypothesis 18 (H_a18): FC in using ITG is positively related to the effort of using ITG.

Alternative Hypothesis 19 (H_a19): Effort of using ITG, is positively related to the actual use of ITG.

Alternative Hypothesis 20 (H_a20): Use of ITG is positively related to DevOps maturity.

Alternative Hypothesis 21 (H_a21): ITG maturity is positively related to the effort to use ITG

Alternative Hypothesis 22 (H_a22): ITG is positively related to DevOps maturity

Alternative Hypothesis 23 (H_a23): Indirectly, DevOps maturity is positively related to the BI to adopt ITG

Applications to Professional Practice

The validation of the hypotheses posited in this study, demonstrate that the adoption of ITG is dependent on external and internal factors including (a) organizational or regulatory compliance, (b) organizational perception of DevOps abilities towards product delivery and organization-wide alignment, and (c) DevOps maturity to deliver according to the organization's expectations. IT leaders managing DevOps teams need to understand the underlying constructs comprising such factors.

A Review of the Validated Hypotheses

PE is Positively Related to the BI to Adopt ITG

The findings of this study demonstrate the PE, specifically extrinsic motivators, positively affect the BI of DevOps leaders towards the adoption of ITG. Therefore, DevOps leaders need to clearly understand the DevOps teams' ability to align with (a) other IT teams and (b) other business departments. Furthermore, DevOps leaders need to understand the organization's expectations and KPIs in measuring DevOps contribution towards the product delivery.

SI is Positively Related to the BI to Adopt ITG

Influence outside of DevOps teams positively influences the BI of DevOps leaders towards the adoption of ITG. Such influence originates from technical and non-technical leaders within the organization who expect specific performance from DevOps teams. To this end, DevOps leaders need to determine these key influencers and ensure that expectations are met.

FC are Positively Related to the USE of ITG

Organizations having access to ITG resources, including training and specialized ITG roles facilitate the use of ITG. Such conditions result in IT leaders finding it easy to adopt and participate in and ITG framework (*EE3*). Specifically, such conditions are:

- Access to necessary resources to adopt and collaborate in an ITG framework.
- Access to necessary knowledge to adopt and collaborate in an ITG framework
- Access to specialized training to adopt and collaborate in an ITG framework
- Access to a specific person (or group) for assistance to adopt and participate in an ITG framework

ITG EXP has a Positive Moderating Effect Between SI and BI to Adopt ITG

The above-mentioned point is further backed by the fact that ITG-certified DevOps leaders advocate for ITG adoption based on external influence (SI) to boost DevOps productivity and alignment with business objectives.

FC in USE of ITG is Positively Related to the Effort of Using ITG

The FC mentioned above, allow DevOps leaders to minimize the effort towards the adoption and use of ITG. This means that DevOps leaders having supporting resources may be able to adopt an ITG framework faster thanks to better advocation. However, such improvements may not translate in faster adoption or reduced ITG-process changes (ITG maturity). On the other hand, experienced DevOps leaders may understand the need to change specific ITG processes faster and proceed to a more mature ITG framework with the end goal to improve DevOps capabilities.

DevOps EXP has a Positive Moderating Effect between SI and BI to adopt ITG

Experienced DevOps leaders understand the capabilities of such teams in terms of self-management, automation, and deployment reliability. When these qualitative and quantitative KPIs are not as per expectations, DevOps leaders advocate towards the adoption of ITG when external stakeholders flag product delivery and DevOps alignment concerns.

Organizational PE to Adopting and Using ITG, is Positively Related to SI from External Key Members in the Organization

Influential people in the organization advocate for ITG adoption with DevOps leaders, especially when the expected performance is not met. Such expectations arise from 3 key areas, specifically:

- Lack of alignment between DevOps teams and other IT teams
- Lack of alignment between DevOps teams and other business departments
- DevOps teams are not delivering end products, as per expectations

Effort of Using ITG, is Positively Related to the USE of ITG

As DevOps leaders dedicate effort addressing the goals of ITG adoption, the participation and use of ITG results in beneficial outcomes, both for the DevOps teams and the organization. DevOps leaders who have a core role in an ITG framework (*USE1*) and consistently participate (*USE4*), and potentially improve ITG processes, experience benefits, specifically:

- clear and understandable role to adopt and collaborate in an ITG framework
- access to necessary resources to adopt and collaborate in an ITG framework

Use of ITG is Positively Related to DevOps Maturity

Immature DevOps teams look at ITG frameworks to accomplish tasks more quickly (*PE2*), thus increasing the productivity of DevOps teams (*PE3*). To this end, DevOps engineers themselves may advocate for the adoption of ITG practices (*SN2*). In such environmental conditions (low DevOps maturity), the adoption and use of an ITG framework, allows IT leaders to improve their DevOps teams capabilities through formalized management structures, such as deployment windows, communication cadences, architectural designs, knowledge sharing, and service management. As DevOps teams familiarize and improve their internal practices through ITG mechanism, the maturity of said teams is likely to improve. Release management is one of the most prominent ITG mechanism adopted by DevOps teams, due to low confidence in the deployments. DevOps leaders need to prioritize quality assurance (QA) and continuous integration (CI) practices towards a continuous deployment status. It takes years of technical and human dedication, as well as a homogenized culture where testing is a vital component in every step of product development and delivery, to achieve excellent practices in the above-mentioned areas.

ITG Maturity is Positively Related to the Effort to USE ITG

Throughout of this study, I determined that most DevOps teams use ad-hoc ITG frameworks. This means that DevOps teams undergo multiple ITG iterations until they achieve a suitable ITG framework which can be used towards improve capabilities. Such ITG changes allows DevOps teams to improve the effort to participate in an ITG framework and permit them to achieve their capabilities with reduced efforts over previous iterations.

ITG Maturity is Positively Related to DevOps Maturity

As DevOps leaders engage in continuous improvement within the adopted ITG framework, the maturity of DevOps teams is positively affected. DevOps maturity is elevated when ITG mechanisms undergo iterations for improvement.

Indirectly, BI to Adopt ITG is Positively Related to Improving DevOps Maturity

Similarly, experience DevOps leaders use ITG mechanisms to improve DevOps maturity through formalized processes thus ensuring support from key stakeholders and effective monitoring and transparency.

Research Answer

Based on all the above validated hypotheses, a cohesive answer toward the research question is formalized as:

Organizational alignment, product performance expectation, and assistance from experienced DevOps executives encourage key stakeholders to push for ITG implementation. Continuous ITG enhancements allow the adoption and use of ITG processes, thereby lowering effort, which results in greater DevOps maturity shown in better alignment, self-management, and product delivery of products.

In this study, I demonstrated that the adoption of ITG is not necessarily driven by IT leaders managing DevOps teams. In fact, IT leaders are heavily influenced to adopt ITG by SI, including executive management, and external (outside of the DevOps teams) PE. However, as DevOps teams' strife to achieve high maturity levels, DevOps and ITG experience influence IT leaders to adopt ITG mechanisms. This means that experienced DevOps leaders understand when the capabilities of their DevOps teams are lacking and require formal processes to improve the management and delivery of such teams

IT Leadership

Knowledge-intensive organizations, such as software organizations, are subject to a high degree of ambiguity. In the absence of high DevOps maturity, ITG provides DevOps leaders with the necessary processes to undertake strategic and tactical activities. This allows technical teams to deliver products according to the organization's expectations. The absence of ITG processes entices IT leaders to engage in the opposite direction, whereby they engage in micro-management activities (Alvesson & Sveningsson, 2003). Such bad leadership results in siloed knowledge and communication barriers thereby promoting fragmented knowledge. IT leaders relying on micro-management or authoritative styles tend to prefer a command-and-control approach towards product delivery, whereby delivery teams prefer an open and empowering setup (Nkukwana & Terblanche, 2017). The former approaches tend to negatively affect team morale (Akkaya, 2021) and creativity (Jassawalla & Sashittal, 2001) which may reduce the organization's agility and innovation towards product delivery. Thanks to cross-functional collaboration, organizations can speed product innovation and delivery while increasing team creativity and cutting expenses. Common characteristics of high-collaboration teams include (a) decentralized decision making, (b) empowerment of team members, (c) creative, (d) acceptance of failures, and (e) cross functional expertise (Jassawalla & Sashittal, 2001). Hence, ITG enables IT leaders to provide the necessary resources to allow DevOps teams to mature in cross-functional collaboration.

Compliance

The findings related to mandatory ITG adoption, as per Table 11, demonstrated that DevOps teams are impacted by overall compliance regulations. Governmental regulatory frameworks, such as the Sarbanes-Oxley Act, and industry-specific regulatory requirements, such as HIPAA and PCI, highlight the importance of ITG initiatives (Debreceny, 2013). From a regulatory and conformance perspective, Tjong et al. (2017) found that ITG allows organizations to improve the conformance and adaptability to ever-changing regulations. Case in point, since 2018, European organizations must streamline their IT processes and systems to conform with GDPR. Failure to do so will result in hefty fines and a debacle in the image of the company (Munier & Kemball-Cook, 2019). This legislation doesn’t only affect EU states but also non-EU states handling data of EU citizens.

Organizational Performance

A key foundation of any ITG framework is the setup of processes aimed at formalizing strategic alignment between the technological and business functions. Such strategic alignment is necessary to increase organizational performance through strategic planning, strategic technological road mapping and product management (Debreceny, 2013). These findings align with Ali's (2020) conclusion that ITG's structure, process, and relational mechanisms positively effect service innovation and organizational performance. PE is a significant predictor in the use of EA (Hazen et al., 2014), business-IT strategic alignment (Chau et al., 2020) and formalized ITG frameworks such as COBIT (Frelinger, 2012).

Product Roadmap

It is widely understood and accepted that the IT strategic role, plays a significant role towards the success of businesses. Borja (2018) identified the need of ITG experience towards the effectiveness of ITG mechanisms. Furthermore, the researcher validated the notion that ITG effectiveness, through strategic, tactical, and operational changes, positively affects product innovation. As organizations prioritize product innovation to achieve their business goals, it is understood that ITG promotes process innovation towards this direction. Oliveira and Rozenfeld (2009) identified technology road mapping (TRM) and project portfolio management (PPM) as necessary towards the improvement of new product development. The involvement of multifunctional stakeholders in the technology roadmap, in conjunction with clear communication, and understanding of the value in TRM changes positively effect product development. Therefore, IT leaders need to easily be able to introduce and adopt such ITG mechanisms toward product roadmap and innovation.

The adoption of an ITG framework such as COBIT requires a considerable effort (Hartono, 2020). Strong top management support, internal ITG expertise, competition utilizing ITG frameworks, and access to external ITG support are critical factors towards ITG adoption identified by Aoun et al. (2011). Amorim et al. (2020) recommended the use of agile practices to adopt COBIT because it increases senior management involvement and facilitated the early detection of scope misalignment in ITG mechanisms.

Agility

Software organizations require agility to compete against competition and deliver innovative products. Vejseli et al. (2018) identified different dimensions which distinguish between agile and traditional ITG. These dimensions comprise structure, process, and relational mechanisms within ITG, whereby agile firms adopt small interdisciplinary lean teams, leveraging transformational leadership as well as delegated decision making through agile practices, such as SCRUM. Furthermore, Vejseli et al. (2018) identified different ITG patterns amongst small and large agile organizations, such as CIO participation in small highly agile organizations as opposed to transformation units in large agile organizations.

Lobera (2021) identified 8 different ITG themes in small manufacturing organizations, specifically following an ITG framework, support organizational goals, alignment between IT and business goals, budget considerations, review of implemented and emerging technologies, collaboration, and improved relations. These ITG themes and motivation align with software delivery organizations, whereby IT leaders leverage ITG to have feedback and control on their product development and delivery.

Erasmus and Marnewick (2021) identified social perspectives related to the adoption of COBIT, specifically, cost and resource management, strategic alignment through EA, personal realization, and effective communication of the IT strategy to the business. ITG enablers facilitating product delivery are categorized into (a) principles, policies, and frameworks, (b) processes, (c) organizational structures, (d) culture, ethics, and behavior, (e) information, (f) services, infrastructure, and applications, and (g) people, skills, and competencies (Henriques et al., 2020). Furthermore, domain specific ITG enablers may be considered key factors towards the adoption of ITG. Henriques et al. (2021) identified data privacy, data protection and data analysis as ITG enablers found in COBIT framework towards successful implementation of IoT.

To measure the effect of external environment on ITG effectiveness, environmental competition, complexity, and rate of change need to be evaluated (Haes & Grembergen, 2008). Abdollahbeigi and Salehi (2019) determined that external factors influence the effectiveness of ITG. Additionally, effective ITG mediates the relationship between external factors and firm performance. Software companies are highly influenced by strong competition, complexity, and continuous changes. Therefore, ITG needs to be adopted to mediate the external factors towards organizational performance.

DevOps Maturity

The aim of ITG adoption is specifically targeted to improve DevOps alignment with IT and non-IT teams whilst improving the delivery of products. IT leaders acknowledge the fact that adoption and use of ITG requires a considerable effort. However, such factor is not significant in the IT leader's intention to adopt ITG. This aligns with the fact that key drivers towards ITG adoption are extrinsically motivated (PE4, PE5, PE6, SN1, SN2, and SN3). On the other hand, facilitating condition are a determining factor in improving the effort to use ITG, supported by a mature ITG framework. Furthermore, the use of ITG in conjunction with a mature ITG framework like ITIL significantly improve the DevOps maturity. Most of the sample used ad-hoc processes, thus confirming that ITG maturity is comprised of frequent changes to the ITG mechanics. This is also supported in the literature review in Section 1. Key indicators towards DevOps maturity denote the internal need to adopt ITG through constructs *PE1*, *PE2*, *PE3* and *SN2*.

Through the findings of this study, I demonstrated that IT leaders managing DevOps teams use evolving ITG mechanisms, that can adapt to changes as they occur. Such changes originate from internal (DevOps maturity) or external factors (SI and PE) towards DevOps maturity. Additionally, communication channels (FC and EE constructs) are used in conjunction with automation are necessary to achieve optimal DevOps maturity (Radstaak, 2019; Vejseli et al., 2018). Throughout this research, I demonstrated that such governance takes the form of ad-hoc framework-based arrangements. The ITG model for DevOps teams as proposed by Greene (2020) comprises the notions of (a) automation of repetitive tasks, (b) organizational restructuring to facilitate continuous delivery of products, (c) collaboration amongst business and DevOps to ensure empowerment and alignment and (d) continuous delivery enabling peer review and the use of a compatible toolset such as containerization, orchestration, automation, and versioning control. The importance of effective ITG is highlighted by Devos and Van (2015) whereby ITG-enabled organizations yield 40% higher returns over non-ITG enabled organizations. This denotes that ITG empowers organizations to be more competitive whilst achieving self-managed and company-wide trust capabilities.

Smith et al. (2021), identified only 26% of organizations as elite in the latest state of DevOps survey. Such a category is characterized by on-demand deployments, less than 1 hour for changes and restore and under 15% of failure rates. The fact that most organizations do not fit in this category, denotes that product delivery is not in its optimal state and hence required formalized governance mechanisms. Such mechanisms are supported by key organizational stakeholders and advocated by experienced DevOps leaders.

Implications for Social Change

Software products provide consumers with the tools or services they need to address complex requirements in a more timely and effective manner. Investigating the relationship between differences in PE, EE, SI, FC, and the intention of IT leaders to adopt ITG in multiproduct DevOps teams, as moderated by AGE, GND, EXP, and VOL, may provide IT leaders with the information they require to adopt ITG. The knowledge presented in this study is important for social change because it has the potential to assist organizations in improving their operational efficiency and effectiveness, as well as generating higher value for their customers and society.

Organizational Culture

Organizational usefulness, trust, role and responsibility alignment, open communication, respect, and perceived behavioral control-internal are key factors identified by Masombuka (2020), to adopt an effective DevOps culture. These factors intersect with the deliverables of an effective IT strategy as identified in the literature review., specifically trust (Henriques et al., 2020), roles (Galup et al., 2020), communication (Radstaak, 2019), and tools (Khumaidi, 2021). Vatanasakdakul et al. (2017) revealed that the ease of use, IT innovation, ITG training, and external pressure all contributed to the success of ITG adoption. Moreover, organizational performance was significantly influenced by factors such as simplicity of use, user satisfaction, and external and executive level support.

Product Quality Toward End Users

ITG provides organizations with the necessary support to implement industry standards and best practices, thus improving their DevOps processes and products (Bollen et al., 2018). Improvement to the product service delivery, positively effects products' uptime, reliability, and functionality. Such gains are important for the public, since product disruptions or lack of functionality, reduce the customer experience and overall service offering. Specifically, reliability is an essential feature of any software as a service (SaaS) offering, whereby the community consumes such services as a commodity as required. These services include banking, entertainment, education, and communication. Hence it is paramount that such services provide the best reliability in terms of performance, features, and security to ensure the safeguarding and optimum product experience for the public.

The general IT problem identified in this study is the lack of ITG amongst DevOps teams within multiproduct delivery organizations. ITG maximizes the value of information technology investments by fostering collaboration between business units and IT teams. Faster time-to-market, higher customer satisfaction, and the capacity to produce products that suit customers' demands quickly, effectively, and efficiently are key advantages that organizations may get by continuously delivering products in a DevOps environment (Greene, 2020). The adoption of ITG tends to improve product/service quality, user satisfaction, and IT management, specifically alignment and planning (Meçe et al., 2020). Therefore, the absence of an effective ITG strategy hinders the continuous delivery of products, which causes a delay in achieving organizational competitiveness (Gill et al., 2018). Furthermore, the lack of an ITG might make it difficult to align the business and information technology, reducing the value of IT.

The adoption of ITG mechanisms, specifically decision-making and accountability enforcement, were proposed by Riemer et al. (2020) to implement a societal-wide collective action towards contact tracing during the COVID-19 pandemic. Decision-making and accountability enforcement satisfy the who and how questions related to implementation and use of a technology or process. This study demonstrates the value in adopting ITG mechanisms at a societal level. Such societal-level governance may allow multiple DevOps teams from different organizations to align product delivery, thus mitigating societal level concerns, like security, uptime, capacity, and cost-effectiveness.

Towards Sustainable IT

As society is becoming increasingly aware of global warming, Green IT is solicited. Environmentally sustainable computing and computing assisted initiatives towards sustainable environment are taxonomies of Green IT. Patón-Romero et al. (2021), used established ITG frameworks to propose a Governance and Management Framework for Green IT (GMGIT). Virtualization, cloud implementations, shutdowns of unutilized applications and metrics monitoring are key strengths and opportunities towards Green IT which fall in the DevOps domain.

Recommendations for Action

A DevOps culture is a combination of Agile and Lean approaches that ensure that product features are continuously delivered with little waste while being monitored by excellent governance controls (Galup et al., 2020). Unfortunately, industry-wide surveys demonstrate that most DevOps teams denote low DevOps capabilities thus impacting the adoption of a true DevOps culture. Professional experience and informal conversations with some of the participants denote similar challenges in multiproduct DevOps teams, specifically:

- Disparate Development and Operations teams
- Non-homogenized blend of technology, people, and processes
- Dissatisfaction with current product delivery
- High cost of ownership for product delivery
- Focus on systems management rather than service management
- Lack of communication and understanding between DevOps and stakeholders
- New products are delivered late and over budget

DevOps teams in this study were predominantly found to adopt ad-hoc ITG framework. Moreover, such teams adopt in some way or form ITIL processes in their ad-hoc frameworks, specifically release management, change management, configuration management, problem management, service design, incident management and problem management. The end goal of adopting service management practices in DevOps teams is aimed at creating a service driven culture within DevOps teams focused on continuous improvement whilst ensuring highest level of security and product delivery.

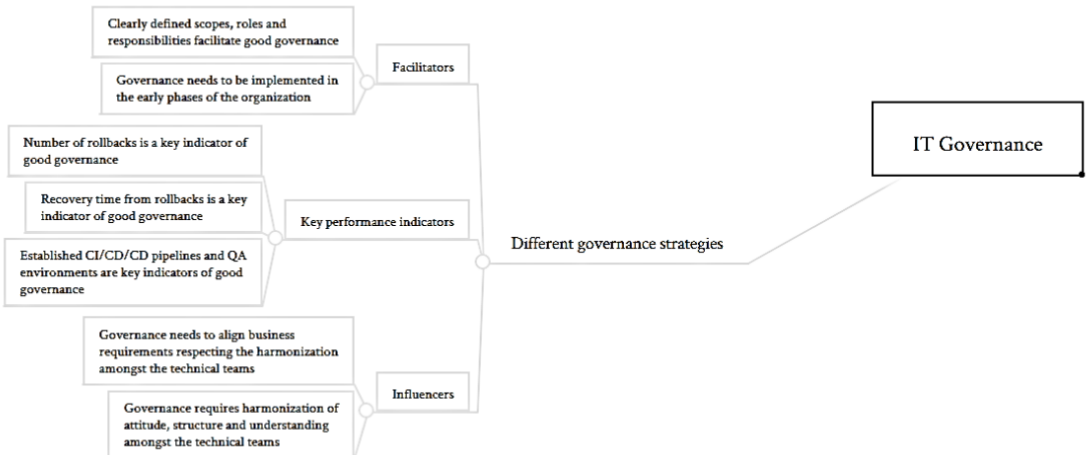
Leaders planning to adopt ITG practices to improve DevOps capabilities need to keep in mind the following critical factors:

1. Senior management support
2. ITG and DevOps expertise
3. Transparency regarding the existing product delivery challenges and expected benefits of adopting ITG
4. ITG adoption should be implemented early in the DevOps transformation, conversely a change in culture both in the organization and the DevOps teams is necessary and more painful
5. Measurable KPIs to determine need of ITG changes and DevOps capabilities.
6. Infrastructure maturity clearly defining established CI/CD pipelines and QA environments

These components are encapsulated in a mind map as per Figure 15.

Figure 15

Key Factors to be Considered by DevOps Leaders when Adopting ITG



The ITG's adoption is contingent on influencers, facilitators, and key performance indicators. Influencers in the adoption of ITG comprise attitude, structure, and alignment of DevOps teams amongst the various technical and non-technical teams. The suitability of the implemented ITG procedures, as well as the present DevOps capabilities, is determined by key performance metrics. The number of rollbacks on production environments, recovery times, and lead time to provide a new product or update are examples of such KPIs. Early adoption of ITG mechanisms, mature DevOps-oriented ITG procedures, and employing experienced ITG and DevOps personnel are key facilitators of successful ITG.

Effective companies use democratic governance, in which all relevant stakeholders have an equal and justifiable voice in overall decisions that are backed by the company and followed by the teams. However, the equilibrium that underpins such democratic governance is precarious and requires ongoing debates and trade-offs. Failure to re-calibrate the governance strategy's structures has a detrimental impact on product delivery KPIs.

Recommendations for Further Study

By means of this study’s findings, I provided an exhaustive answer to the research question, whereby key stakeholders advocate for ITG deployment due to organizational alignment, product performance expectations, and motivated by experienced DevOps leaders. Because of continuous ITG improvements, DevOps maturity increases in improved alignment, self-management, and product delivery. The need to broaden the body of knowledge to include aspects that contribute to enhanced product delivery, as well as ITG adoption and DevOps maturity, opens new avenues for study. To this end, four key topics for future study are recommended hereunder.

SCRUM and ITG Coexistence Toward DevOps Maturity

In this study, I found that a minority of the sample respondents (2.5%) consider Scrum and Kanban as a standalone ITG framework to manage DevOps teams, as per table 10. This finding aligns with the results of Wiedemann (2018), whereby DevOps teams use either Kanban or Scrum as an agile approach to manage DevOps teams. Such teams comprise of software developers, software engineers, and participation of one or many product owners. Conversely, Amorim et al. (2020) used Scrum to implement COBIT procedures, which improved ease of perception, ease of use, usefulness for the business and individuals, and goal efficacy. Future research should explore how DevOps leaders consider Scrum or Kanban processes in the context of ITG and DevOps maturity. Potential research questions may include:

1. Do Scrum and ITG replace each other, or they complement each other?
2. As Scrum leverages the product owner role, do key ITG expectations (trust, communication, facilitation) become a bottle neck on the product owner?
3. How are ITG expectations and deliverables handled in multiproduct DevOps teams which participate with multiple Product Owners?

Effect of DevOps Maturity Effect on BI to Adopt ITG

Smith et al. (2021) found that most companies have not yet achieved a high level of DevOps maturity. My study found an indirect correlation between DevOps maturity and BI by DevOps leaders to adopt ITG. This finding requires greater exploration, utilizing alternative constructs from internal DevOps' PE and SI. Furthermore, in a UTAUT context, DevOps maturity should be investigated as an independent variable rather than a dependent one. The notion of DevOps maturity may also be closely associated to trust, as identified by Riemer et al. (2020), as an influencing variable in ITG adoption. Collaboration and collaboration across development and operations teams is crucial for a successful DevOps transformation. According to Radstaak (2019), a DevOps maturity model may be used to verify an organization's DevOps function's capabilities. The objective of such approach is to aid businesses obtaining an optimal level while exhibiting other department actionable things towards developing a DevOps culture.

Organizational Achievement of Elite DevOps Capabilities

In this study, I demonstrated that adoption of ITG has a positive effect on DevOps maturity, defined as internal PE and SI. However, DevOps maturity comprises multiple facets including technical, people and organizational KPIs. It is confirmed by Winkler and Wulf (2019) that IS-business alignment mediates and reinforces ITSM competency. Companies with conservative IT strategies might gain the most from using ITSM. Conversely, agile-driven enterprises need to ensure that ITSM practices does not clash with flexibility and innovation. Soft governance was suggested by Smits and van Hillegersberg (2018) as a means of bridging the theoretical and practical ITG gaps, and a new ITG maturity model was developed to account for both hard and soft ITG. It was discovered that there are many ITG maturity models, including (a) the COBIT, (b) the MIG, (c) the 12 action areas, (d) the nine ITG categories, (e) the Green IT capability maturity model, and (f) the COBIT in combination with ITIL, TOGAF, and other frameworks. The Maturity ITG (MIG) model was regarded as the most thorough in encompassing hard and soft ITG topics. Soft governance elements which may affect the adoption of ITG include (a) continual development of the ITG process which relates with the motive of agile ITG, (b) leadership support, (c) involvement, and (d) understanding and trust. These topics were found and addressed in prior research. Masombuka (2020), leveraged the Information System Development Model to design a framework for the implementation of a DevOps culture via the identification of important success elements. Open communication, duties and responsibilities, respect and trust are the crucial success characteristics that create a DevOps culture. Future research should consider alternative theoretical and conceptual frameworks to understand how IT leaders can improve their DevOps maturity.

Validating the Modified UTAUT Model for ITG Adoption in DevOps Teams

I used the modified UTAUT model which featured a novel configuration of UTAUT constructs as well as dependent and independent variables, as per Figure 12. This revision was necessary to understand the correlation between DevOps leaders' BI to adopt and actual use of ITG. Although the model has achieved construct reliability and model fitness, future research should revisit such model and validate or propose changes to it.

Reflections

The endeavor of acquiring a Doctorate degree is incredibly rigorous. Time management, self-motivation and endurance are necessary to undertake such a pursuit. As I progressed throughout this journey, it was evident that obtaining a Doctorate in Information Technology was not an extension of my master's in information systems and Technology. The expected quantity and quality of work in a DIT program is far greater. Luckily for me, I had a clear research topic in my mind since the early stages of my doctoral journey. Hence, I consistently used the theoretical practices requested in the various modules to explore my research question. The culmination of four years of research is presented in this document and I hope I have added valuable knowledge to the body of research.

When I started researching this topic, my personal bias was derived from experience working within multiple DevOps teams. However, I demonstrated that DevOps teams are not silos and are highly dependent on external influences as evidenced by the strong positive significance of SI and organizational PE towards DevOps teams. Frequent discussions with other DevOps leaders always led me to believe that DevOps maturity is mostly dependent on experience and technology. However, this study showed that DevOps maturity is determined both from internal and external actors. Influential people in the organization, who may not be part of the DevOps have a high effect on the preconception and expectancy of DevOps teams. Therefore, applying generalization to factors towards DevOps maturity is not that simple. After all, organizations differ in the way they adopt DevOps within their IT departments.

Future doctoral candidates should not underestimate the data collection process, especially in random survey quantitative study. During such process, the researcher needs to be persistent, resourceful, and flexible. In my experience, posting a message on multiple LinkedIn groups, required follow ups with several participants in the groups. Also, do expect positive and negative feedback from respondents about the research. Furthermore, I strongly encourage future candidates to gather more respondents than the recommended results obtained from sample calculation, simply because the theoretical model might require changes as analysis is undertaken.

Summary and Study Conclusions

The central theme of this study was to understand the relationship between BI to adopt ITG for multiproduct DevOps teams and PE, EE, SI, and FC, as moderated by GND, AGE, EXP, and VOL.

A quantitative partial least squares analysis was used in this research to better understand the variables that influence the adoption of ITG techniques for multiproduct DevOps teams. The UTAUT model served as the theoretical basis for this research, which examined the link between BI to embrace ITG and PE, EE, SI, and FC.

As I conducted my data collection process, a particular moderator in a LinkedIn group challenged the value of my research. Agile evangelists and proponents are irritated by the concept of utilizing ITG in DevOps teams. After all, the whole concept of a DevOps culture is based on self-organizing and self-managing teams which is inimical to a trust-based agile workplace. Achieving this level of maturity requires time and effort and unfortunately DevOps surveys demonstrate that 75% of DevOps teams are still nowhere close to this stage (Smith et al., 2021). Diverse development and operations teams are key indicators of an underdeveloped DevOps culture. Another feature of immature DevOps culture is the employment of a heterogeneous mix of technology, people, and procedures. Such issues lead to organizational discontent with present product delivery and excessive product ownership costs. Furthermore, such DevOps teams are associated with a lack of communication and understanding with stakeholders and an emphasis on systems administration rather than service management. Finally, an inexperienced DevOps team delivers new products late and over budget.

By undertaking this study, I demonstrated that key stakeholders advocate for ITG adoption due to organizational alignment, product performance expectations, and support from experienced DevOps leaders. Continuous ITG enhancements, supported by FC, enable the adoption and exploitation of ITG processes, decreasing effort and resulting in increased DevOps maturity as seen by improved alignment, self-management, and product delivery.

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Appendix A: Permission of UTAUT Author to Use Model, Instrument, and Images

GD **Gordon Davis** Yesterday at 18:54

Re: Permission to use instrument and images in UTAUT published work

To: Russell Camilleri,

Resent-From: Russell Camilleri

Yes, of course you can.

On Tue, Sep 21, 2021 at 4:53 AM Russell Camilleri [redacted] wrote:

> Dr. Davis,
>
> I am a DIT student at Walden University and am writing a doctoral study on the adoption of IT governance strategies for multi-product DevOps teams.
> I would like to use the Unified Theory of Acceptance and Use of Technology to study my topic.
>
> May I have your permission to use the instrument and images contained in your published work:
> Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of Information Technology: Toward a unified view. MIS Quarterly, 27(3), 425. https://doi.org/10.2307/30036540
>
> Thank you for your consideration in advance,
>
> Russell Camilleri

--

Gordon B Davis, Professor Emeritus of Information Systems

Carlson School of Management - University of Minnesota

Appendix B: Permission of UTAUT Publisher to Use Model, Instrument, and Images

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This is a License Agreement between Russell Camilleri ("User") and Copyright Clearance Center, Inc. ("CCC") on behalf of the Rightsholder identified in the order details below. The license consists of the order details, the CCC Terms and Conditions below, and any Rightsholder Terms and Conditions which are included below.

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Appendix C: Permission of Author to Use Table in UTAUT Published Work

AC Andreas Chang
Tue 9/21/2021 12:16 PM
To: Russell Camilleri

Dear Mr. Camilleri,
Thank you for your enquiry.
Certainly, Sir. You can you it.
All the best,
Warmest regards,
Andreas Chang

...

RC Russell Camilleri
Tue 9/21/2021 12:01 PM
To:

Mr. Chang,

I am a DIT student at Walden University and am writing a doctoral study on the adoption of IT governance strategies for multi-product DevOps teams.

I would like to use the Unified Theory of Acceptance and Use of Technology to study my topic.

May I have your permission to use table 1 (The core constructs of UTAUT) in your published work:

Chang, A. (2012). UTAUT and UTAUT 2: A review and agenda for future research. The Winners, 13(2), 10. https://doi.org/10.21512/tw.v13i2.656

Thank you for your consideration in advance,

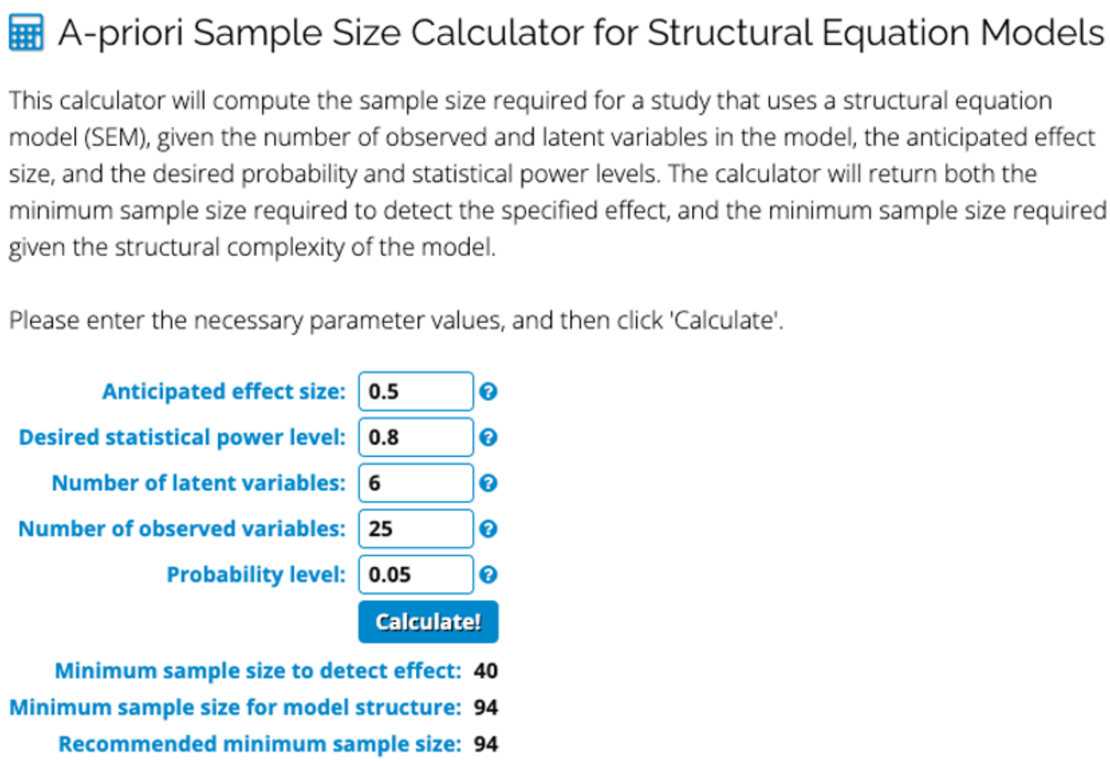
Russell Camilleri

Appendix D: Structural Equation Modelling Sample Size Calculator

The calculator from Soper (2021) was used to determine the recommended sample size for the PLS-SEM model.

Figure 16

Proposed Sample Size for Structural Equation Modelling



A-priori Sample Size Calculator for Structural Equation Models

This calculator will compute the sample size required for a study that uses a structural equation model (SEM), given the number of observed and latent variables in the model, the anticipated effect size, and the desired probability and statistical power levels. The calculator will return both the minimum sample size required to detect the specified effect, and the minimum sample size required given the structural complexity of the model.

Please enter the necessary parameter values, and then click 'Calculate'.

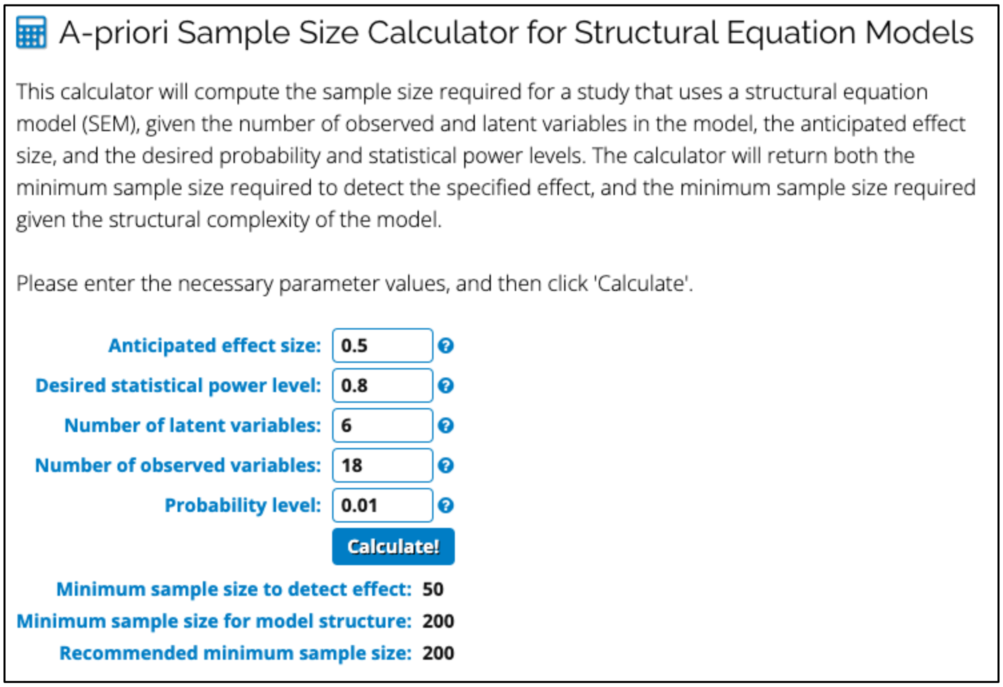
Anticipated effect size:	0.5
Desired statistical power level:	0.8
Number of latent variables:	6
Number of observed variables:	25
Probability level:	0.05

Calculate!

Minimum sample size to detect effect:	40
Minimum sample size for model structure:	94
Recommended minimum sample size:	94

Figure 17

Revised Sample Size for Reliable UTAUT Model



Appendix E: Normality Tests

Table 33

Descriptive Statistics of the Constructs

Construct	Mean	Std. deviation	Corrected item-total correlation	Cronbach's alpha if Item Deleted
PE1	4.00	0.902	0.535	0.933
PE2	4.02	0.888	0.511	0.934
PE3	3.77	1.021	0.586	0.933
PE4	4.55	0.730	0.769	0.929
PE5	4.64	0.622	0.725	0.930
PE6	4.52	0.777	0.731	0.930
EE1	4.72	0.549	0.741	0.931
EE2	4.54	0.731	0.770	0.929
EE3	4.56	0.681	0.570	0.932
EE4	3.79	0.960	0.550	0.933
SN1	4.64	0.480	0.494	0.933
SN2	3.81	1.033	0.606	0.933
SN3	4.59	0.493	0.322	0.935
SN4	4.65	0.477	0.439	0.934
FC1	4.72	0.549	0.736	0.931
FC2	4.54	0.731	0.766	0.929
FC3	4.43	0.781	0.683	0.931
FC4	4.45	0.782	0.695	0.930
BI1	4.64	0.63	0.590	0.932
BI2	4.62	0.642	0.576	0.932
BI3	4.63	0.664	0.586	0.932
USE1	4.61	0.596	0.792	0.930
USE2	3.22	0.513	0.120	0.937
USE3	3.19	0.558	0.144	0.937
USE4	4.63	0.592	0.744	0.930

Table 34

Skewness and Kurtosis Test

Variable	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
PE1	205	-0.364	0.17	-0.956	0.338
PE2	205	-0.430	0.17	-0.818	0.338
PE3	205	-0.213	0.17	-1.140	0.338
PE4	205	-1.668	0.17	2.341	0.338
PE5	205	-1.548	0.17	1.206	0.338
PE6	205	-1.657	0.17	2.140	0.338
EE1	205	-1.823	0.17	2.382	0.338
EE2	205	-1.630	0.17	2.235	0.338
EE3	205	-1.240	0.17	0.213	0.338
EE4	205	-0.105	0.17	-1.123	0.338
SN1	205	-0.605	0.17	-1.650	0.338
SN2	205	-0.285	0.17	-1.140	0.338
SN3	205	-0.370	0.17	-1.882	0.338
SN4	205	-0.651	0.17	-1.592	0.338
FC1	205	-1.823	0.17	2.382	0.338
FC2	205	-1.630	0.17	2.235	0.338
FC3	205	-1.370	0.17	1.409	0.338
FC4	205	-1.428	0.17	1.522	0.338
BI1	205	-1.567	0.17	1.222	0.338
BI2	205	-1.485	0.17	0.951	0.338
BI3	205	-1.553	0.17	1.021	0.338
USE1	205	-1.293	0.17	0.645	0.338
USE2	205	0.277	0.17	-0.093	0.338
USE3	205	0.037	0.17	-0.138	0.338
USE4	205	-1.392	0.17	0.909	0.338
Valid N (listwise)	205				

Table 35

Tests of Normality

Variable	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PE1	<.001	0.227	205	<.001	0.838	205
PE2	<.001	0.225	205	<.001	0.838	205
PE3	<.001	0.194	205	<.001	0.859	205
PE4	<.001	0.399	205	<.001	0.648	205
PE5	<.001	0.438	205	<.001	0.601	205
PE6	<.001	0.394	205	<.001	0.651	205
EE1	<.001	0.463	205	<.001	0.553	205
EE2	<.001	0.393	205	<.001	0.656	205
EE3	<.001	0.406	205	<.001	0.655	205
EE4	<.001	0.224	205	<.001	0.854	205
SN1	<.001	0.415	205	<.001	0.606	205
SN2	<.001	0.207	205	<.001	0.853	205
SN3	<.001	0.387	205	<.001	0.624	205
SN4	<.001	0.420	205	<.001	0.601	205
FC1	<.001	0.463	205	<.001	0.553	205
FC2	<.001	0.393	205	<.001	0.656	205
FC3	<.001	0.346	205	<.001	0.712	205
FC4	<.001	0.358	205	<.001	0.700	205
BI1	<.001	0.441	205	<.001	0.596	205
BI2	<.001	0.433	205	<.001	0.611	205
BI3	<.001	0.444	205	<.001	0.589	205
USE1	<.001	0.414	205	<.001	0.644	205
USE2	<.001	0.401	205	<.001	0.682	205
USE3	<.001	0.365	205	<.001	0.729	205
USE4	<.001	0.424	205	<.001	0.628	205

Figure 18

Histogram of USE2 Variable

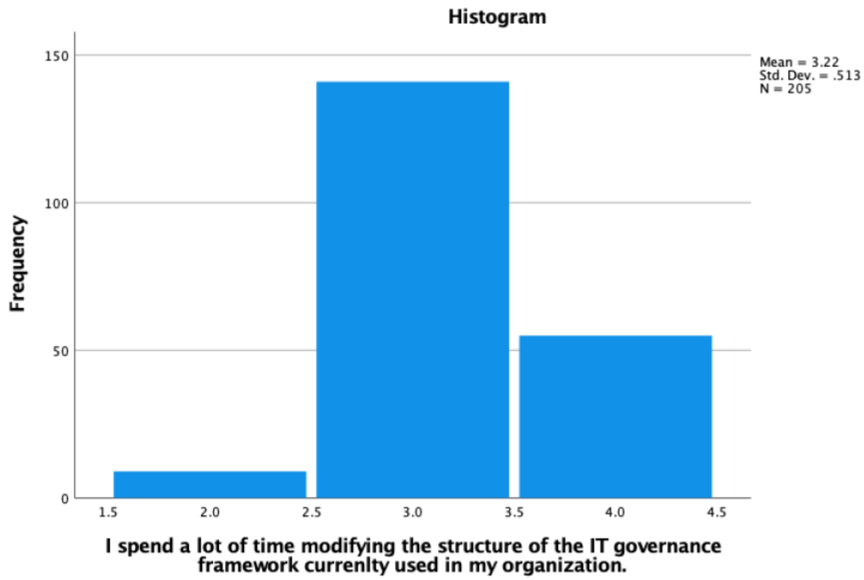


Figure 19

Normal Probability Plot for USE2 Variable

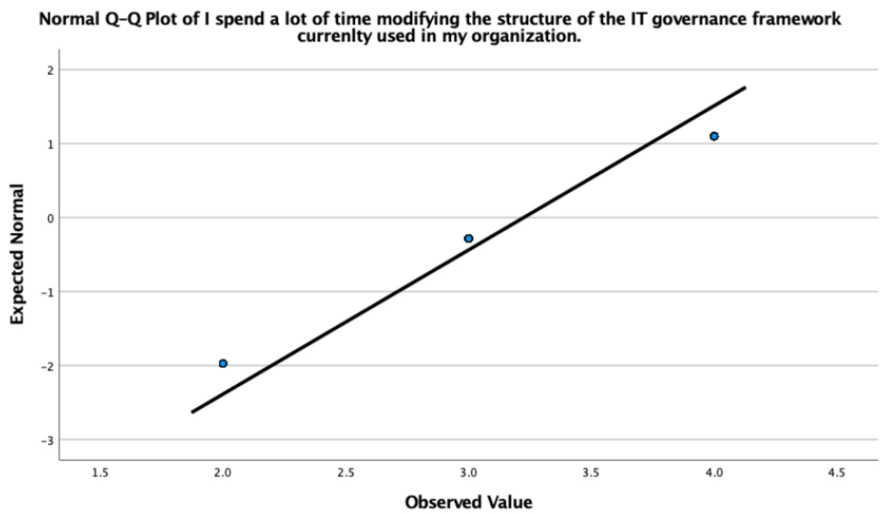


Figure 20

Histogram of BI3 Variable

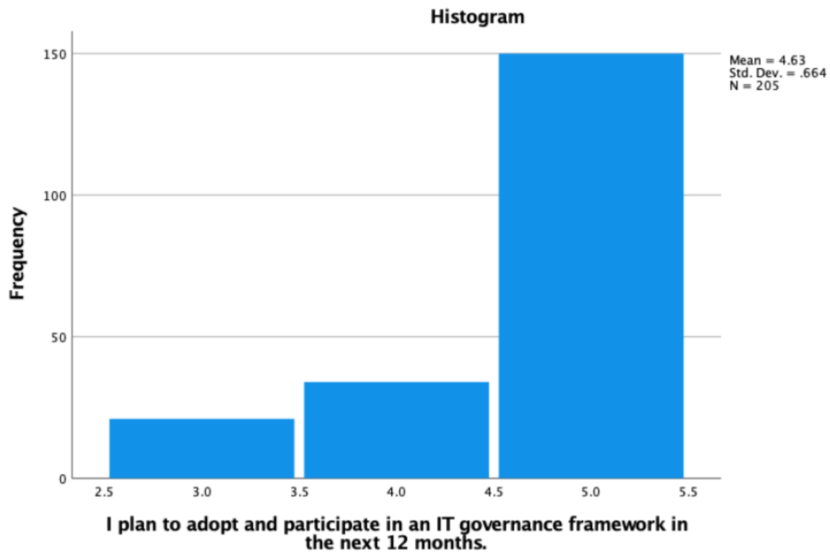


Figure 21

Normal Probability Plot for BI3 Variable

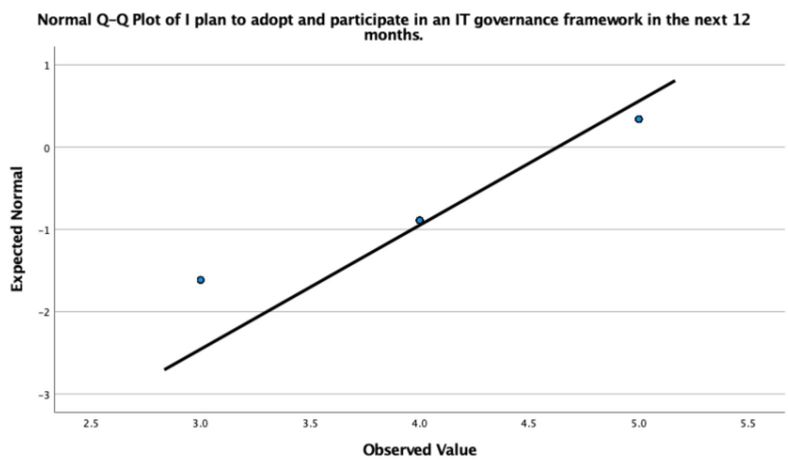


Figure 22

Histogram of USE4 Variable

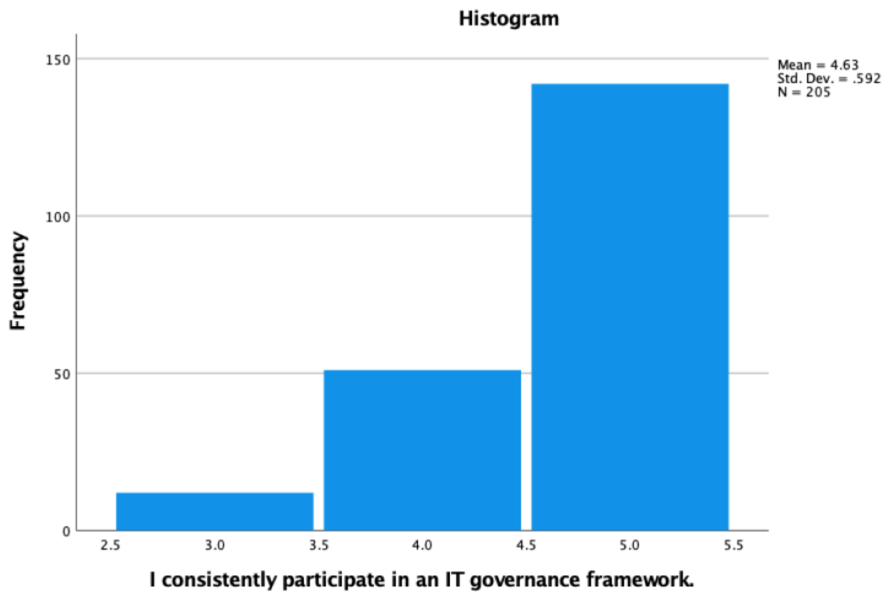


Figure 23

Normal Probability Plot for USE4 Variable

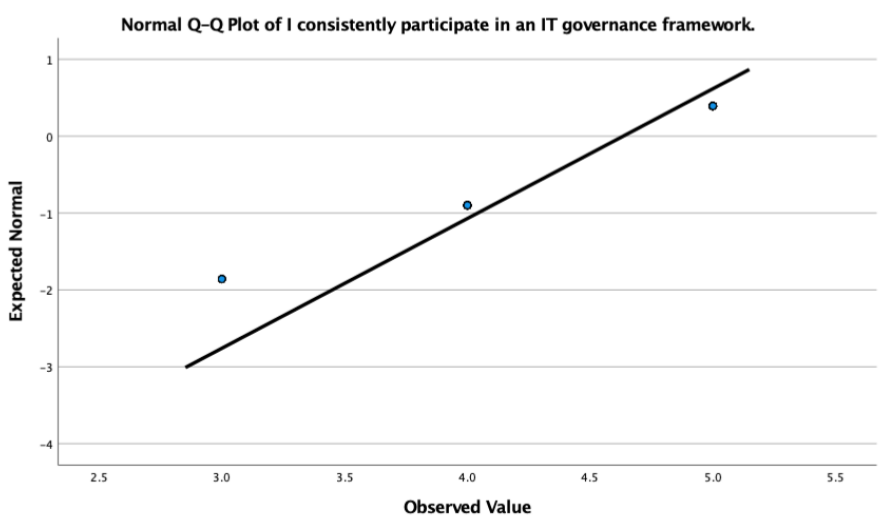


Figure 24

Histogram of PE6 Variable

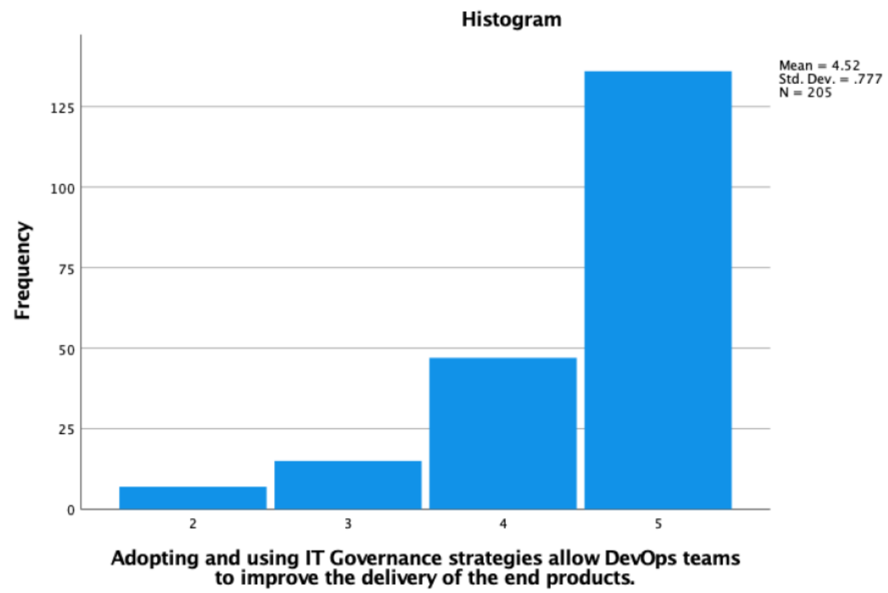


Figure 25

Normal Probability Plot for PE6 Variable

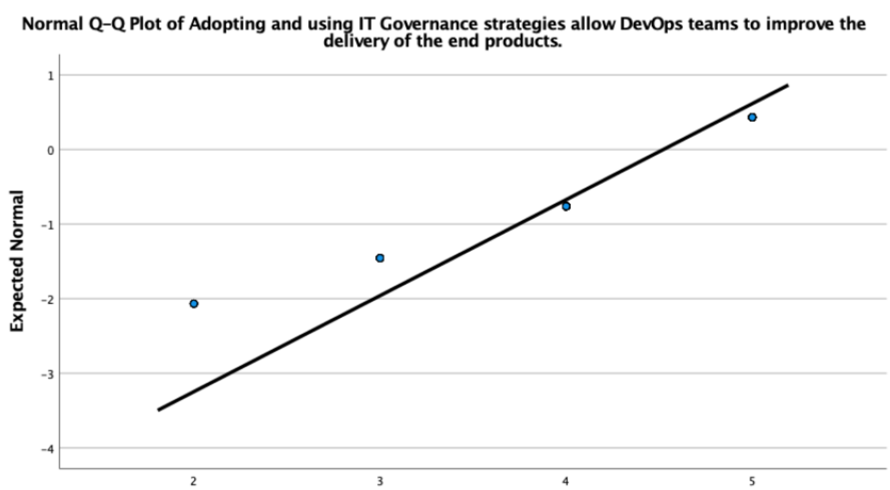


Table 36

Split-half Coefficient Test

Cronbach's Alpha	Part 1	Value	0.894
		N of Items	13
	Part 2	Value	0.887
		N of Items	12
	Total N of Items		25
Correlation Between Forms			0.772
Spearman-Brown Coefficient	Equal Length		0.872
	Unequal Length		0.872
Guttman Split-Half Coefficient			0.852

Table 37

Nonparametric Correlations Analysis for PE Variables

			PE1	PE2	PE3	PE4	PE5	PE6
Spearman's rho	PE1	Correlation Coefficient	1	.970**	.715**	.289**	.219**	.310**
		Sig. (2-tailed)	.	<.001	<.001	<.001	0.002	<.001
		N	205	205	205	205	205	205
	PE2	Correlation Coefficient	.970**	1	.714**	.278**	.213**	.293**
		Sig. (2-tailed)	<.001	.	<.001	<.001	0.002	<.001
		N	205	205	205	205	205	205
	PE3	Correlation Coefficient	.715**	.714**	1	.278**	.241**	.310**
		Sig. (2-tailed)	<.001	<.001	.	<.001	<.001	<.001
		N	205	205	205	205	205	205
	PE4	Correlation Coefficient	.289**	.278**	.278**	1	.688**	.738**
		Sig. (2-tailed)	<.001	<.001	<.001	.	<.001	<.001
		N	205	205	205	205	205	205
	PE5	Correlation Coefficient	.219**	.213**	.241**	.688**	1	.528**
		Sig. (2-tailed)	0.002	0.002	<.001	<.001	.	<.001
		N	205	205	205	205	205	205
	PE6	Correlation Coefficient	.310**	.293**	.310**	.738**	.528**	1
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	.
		N	205	205	205	205	205	205

Table 38

Nonparametric Correlations Analysis for Outliers

			PE1	PE2	PE3	EE2	EE4	SN2	USE2	USE3
Spearman's rho	BI1	Correlation Coefficient	.164*	.155*	.226**	.537**	.227**	.239**	-0.027	-0.007
		Sig. (2-tailed)	0.019	0.026	0.001	<.001	0.001	<.001	0.699	0.923
		N	205	205	205	205	205	205	205	205
	BI2	Correlation Coefficient	.157*	.150*	.176*	.561**	.176*	.204**	-0.022	-0.033
		Sig. (2-tailed)	0.025	0.032	0.012	<.001	0.012	0.003	0.757	0.642
		N	205	205	205	205	205	205	205	205
	BI3	Correlation Coefficient	.141*	0.131	0.136	.472**	0.113	.163*	-0.055	-0.048
		Sig. (2-tailed)	0.044	0.061	0.052	<.001	0.107	0.019	0.432	0.495
		N	205	205	205	205	205	205	205	205
	USE1	Correlation Coefficient	.313**	.301**	.305**	.958**	.276**	.335**	-0.011	-0.01
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	0.876	0.884
		N	205	205	205	205	205	205	205	205
	USE2	Correlation Coefficient	0.048	0.011	.220**	-0.037	.223**	.177*	1	.858**
		Sig. (2-tailed)	0.492	0.873	0.002	0.602	0.001	0.011	.	<.001
		N	205	205	205	205	205	205	205	205
	USE3	Correlation Coefficient	0.063	0.029	.291**	-0.037	.291**	.250**	.858**	1
		Sig. (2-tailed)	0.372	0.676	<.001	0.597	<.001	<.001	<.001	.
		N	205	205	205	205	205	205	205	205
	USE4	Correlation Coefficient	.304**	.291**	.296**	.893**	.266**	.324**	0.009	0.01
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	0.896	0.882
		N	205	205	205	205	205	205	205	205

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Appendix F: Exploratory Factor Analysis

Table 39

Rotated Component Matrix

Rotated Component Matrix[a]					
	Component				
	1	2	3	4	5
PE1	0.174	0.030	0.889	0.070	-0.061
PE2	0.169	0.022	0.884	0.049	-0.096
PE3	0.086	0.117	0.910	0.112	0.227
PE4	0.754	0.197	0.107	0.502	-0.058
PE5	0.490	0.739	0.099	0.238	-0.044
PE6	0.362	0.160	0.150	0.877	0.013
EE1	0.780	0.424	0.152	0.162	-0.004
EE3	0.186	0.247	0.058	0.800	-0.090
EE4	0.060	0.133	0.878	0.092	0.205
SN1	0.131	0.768	0.143	0.108	-0.096
SN2	0.108	0.129	0.913	0.119	0.197
SN3	-0.001	0.692	0.067	-0.003	0.084
SN4	0.100	0.744	0.019	0.172	-0.063
FC1	0.786	0.398	0.147	0.176	-0.001
FC2	0.756	0.185	0.111	0.504	-0.066
FC3	0.319	0.146	0.112	0.879	0.056
FC4	0.319	0.153	0.115	0.890	0.069
BI1	0.359	0.680	0.087	0.183	0.019
BI2	0.389	0.743	0.035	0.101	0.016
BI3	0.329	0.717	0.051	0.211	0.006
USE1	0.830	0.209	0.179	0.361	0.018
USE2	0.002	-0.031	0.117	0.002	0.929
USE3	-0.022	-0.015	0.186	0.004	0.919
USE4	0.817	0.217	0.179	0.279	0.041

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Table 40

Component Transformation Matrix

Component Transformation Matrix					
	Component				
	1	2	3	4	5
1	0.619	0.508	0.337	0.495	0.025
2	-0.178	-0.243	0.88	-0.144	0.337
3	-0.156	0.756	0.076	-0.631	-0.007
4	-0.073	0.130	-0.314	0.125	0.929
5	-0.745	0.308	0.084	0.566	-0.149

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Table 41

Exploratory Factor Analysis After Removing EE2 Variable

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.803
Bartlett's Test of Sphericity	Approx. Chi-Square	7549.935
	df	276
	Sig.	.000