FACTORS THAT INFLUENCE DIGITAL SUPPLY CHAIN PRACTICES MEDIATED BY STAKEHOLDERS' INTENTION IN HIGHER EDUCATION INSTITUTES OF THE LEAST DEVELOPED COUNTRIES

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Abstrak

Wujud pemahaman yang terhad mengenai faktor yang mempengaruhi amalan Rantaian Bekalan Digital (DSC) di Institut Pengajian Tinggi (HEIs) Bangladesh. Objektif utama kajian ini adalah mengenal pasti penentu yang mempengaruhi niat penggunaan DSC dalam kalangan pihak berkepentingan di HEIs, menentukan hubungan penentu ini dengan amalan DSC, dan menyiasat peranan pengantara niat penggunaan DSC dalam hubungan ini. Data dikumpul daripada 434 responden yang dipilih menggunakan teknik persampelan rawak mudah. Kajian ini menggunakan pendekatan Model Persamaan Berstruktur Kuasa Dua Terkecil Separa (PLS-SEM) untuk analisis data. Lima faktor telah dikenal pasti mempengaruhi niat penggunaan DSC pihak berkepentingan: celik digital (DL), syarat pemudah (FC), nilai pemudah (FV), jangkaan prestasi (PE) dan kepercayaan (T). Didapati bahawa niat penggunaan DSC menjadi pengantara hubungan antara faktor-faktor yang dikenal pasti tersebut dan amalan DSC dalam kalangan pihak berkepentingan di HEIs Bangladesh. Penemuan menunjukkan hubungan positif antara DL, FC, FV, PE, T, dan niat penggunaan DSC. Selain itu, niat penggunaan DSC didapati memberi kesan positif kepada amalan DSC di HEIs. Analisis pengantaraan mengesahkan bahawa niat penggunaan DSC adalah signifikan untuk menjadi pengantara perhubungan antara DL, FC, FV, PE, T dan amalan DSC. Penemuan ini memberikan pandangan berharga bagi penggubal dasar dan pengamal dalam sektor pendidikan tinggi dengan menonjolkan kepentingan meningkatkan literasi digital, mewujudkan suasana yag kondusif, menggalakkan nilai DSC, dan membina kepercayaan dalam kalangan pihak berkepentingan untuk memudahkan penggunaan amalan DSC. Implikasi keputusan, hala tuju penyelidikan masa depan, cadangan, dan kesimpulan kajian ini telah dibincangkan dengan teliti dalam tesis ini.

Kata kunci: Rantaian Bekalan Digital, Institut Pengajian Tinggi, UTAUT2, Literasi Digital, PLS-SEM

Abstract

There is limited understanding regarding factors influencing Digital Supply Chain (DSC) practices in Higher Education Institutes (HEIs) of Bangladesh. The primary objectives are to identify the determinants influencing DSC usage intentions among stakeholders of HEIs, determine the relationship of these determinants with DSC practices, and investigate the mediating role of DSC usage intention in these relationships. Data was collected from 434 respondents selected using a simple random sampling technique. The study employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach for data analysis. Five factors were identified as influencing stakeholders' DSC usage intentions: digital literacy (DL), facilitating conditions (FC), facilitating value (FV), performance expectancy (PE), and trust (T). It was found that DSC usage intention mediates the relationship between these identified factors and DSC practices among the stakeholders in Bangladesh's HEIs. The findings revealed positive relationships among DL, FC, FV, PE, T, and DSC usage intention. Moreover, DSC usage intention was found to positively affect DSC practices in HEIs. Mediation analysis confirmed that DSC usage intention significantly mediated the relationships between DL, FC, FV, PE, T, and DSC practices. These findings provide valuable insights for policymakers and practitioners in the higher education sector by highlighting the importance of enhancing digital literacy, creating favorable conditions, promoting the value of DSC, and building trust among stakeholders to facilitate the adoption of DSC practices. The implications of these results, future research directions, recommendations, and conclusions are thoroughly discussed in the thesis.

Keywords: Digital Supply Chain, Higher Education Institutes, UTAUT2, Digital Literacy, PLS-SEM

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CHAPTER ONE

INTRODUCTION

1.1 General Background

A Supply Chain (SC) is an extended network of every individual, organization, resource, operating force, and technology that is involved in the creation and distribution of a product, from the supplier to the producer of source materials, to the final supplier and the end-user (Harcourt & Harcourt, 2018). The manufacturing SC is defined as an operation that adds value to the content by using various capacities, thereby making different uses of this material possible (Benachio et al., 2019). Many researchers gradually executed broad-spectrum research on Supply Chain Management (SCM) in many application domains over the past decades. The majority of these studies clustered on the SCM issues for commercial profit-oriented organizations, such as the manufacturing industry (Shaharudin et al., 2018). Managing the supply chain serves numerous purposes, for example, adding value, producing substantial results, and enriching product visibility. It also helps in the optimization of processes, increasing sustainable profits, enhancing customer satisfaction, improving outsourcing, developing the demand rank of E-commerce, growing globalization, and dealing with the difficulty of the latest dynamics (Uvet, 2020; Sindi & Roe, 2017).

The departmental units in Higher Education Institutions (HEIs) and their operations can also be identified as the Service Supply Chain (SSC). The aim of this 'academic supply chain' is to enhance the value of educational services to the ultimate customer, as the students, employers, and society as a whole (Habib & Hasan, 2019). This digital supply chain (DSC) in the educational sector can act as the new modern supply chain in academia. Integrating digital technology within academic institutions can ensure collaboration and increase performance among the academic supply chain's external and internal entities in the education industry. In fact, some previous studies discussed how the DSC has a significant impact on every stakeholder in the academic industry (Morien, 2019).

The digitally enabled academic supply model can provide a specific guideline for academic institutes to ensure seamless collaboration among their stakeholders and enhance service quality and digital integration (Bates, 2019). For example, institutions adopting the DSC model can provide extensive facilities for managing the staff and students through multi-faceted challenges, such as the complicated processes of registration and add-drop that can be made less hectic for students when done online as opposed to doing it manually. Even in-class lectures may also be forgone for the online teaching and learning model, which not only improves time management but the quality of education as well (Morien, 2019). Furthermore, the top management of the university or board of trustees is able to monitor, coordinate, and supervise the overall operations from home.

The impact of adapting DSC practices can also be seen at the macro level. The DSC can initiate national and international collaboration among HEIs. It enables a robust management system to facilitate inbound and outbound mobility programs, transcending borders virtually. Besides, the DSC expands the reach and scope for long-term collaborative international projects with various other HEIs worldwide. And with proper utilization, DSC can empower HEIs to proactively pursue higher quality standards and improve performance, capitalizing on budget allocations while building a strong brand image and goodwill for the institution.

From the aforementioned paragraphs, it can be understood that incorporating the DSC in academia is imperative. Over the years, HEIs have evolved, doing more with less. HEIs play pivotal roles in the growth and development of the economy in IR 4.0. Even the service preferences of the stakeholders have changed due to the emergence of digitalization in the academic landscape. The application of DSC in HEIs within developed countries has already peaked in the progression of advanced technology integration (Gopalakrishnan, 2015). However, HEIs in Bangladesh still face several obstacles in adapting and utilizing a DSC due to financial constraints and limited economic resources; thus, higher education remains underinvested in Bangladesh (Paul et al., 2021; Jiang et al., 2019).

1.1.1 Issues related with DSC practice in HEIs of Bangladesh

Bangladesh, as one of the least developed countries, faces numerous challenges. These challenges include low human capital, an unstable economic environment, and an ineffective infrastructure (Shohel et al., 2021). These conditions pose significant obstacles to the digital transition of HEIs. The digitalization of HEIs can significantly enhance their operational efficiency and effectiveness, but the necessary steps to achieve this transformation are not yet fully understood or applied.

According to a recent census report, the Bangladesh's current population is 165,158,616 (165 million 58 thousand 616). Out of which, 10 (ten) percent of the total population belongs to 15-19 age group, 9 (nine) percent are in 20-24 group and 8.71

percent are in 25-29 group. It is evident that a major chunk of the population is youth. On average, every year 2 million people join the workforce (Rahman, 2022). There are 157 universities in Bangladesh where 12,30,198 students are enrolled (University Grants Commission of Bangladesh, 2020). Affordability, Poverty, Digital literacy, Physical infrastructure, insufficient logistical support, Infrastructure costs, and many other phenomena were identified as the drawbacks of digitization in countries like Bangladesh and eventually they also impact on higher education institutions (International Telecommunication Union, 2020, The World Bank, n.d., UNESCO, 2018, Zelezny-Green et al., 2018). Data presented in previous sections, like, Digital Adoption Index (DAI), ICT Development Index (IDI) and Digital Readiness Score 2019 are also reflection on this issue. Hence, the scope of this study is narrowed down on the higher education institutes of Bangladesh.

Sayed and Mamun-ur-Rashid (2021), in their study, found that of citizens of Bangladesh struggles to avail ICT aided services due to their low digital literacy. Similar observation was also found in other separate studies where digital literacy was identified as a crucial contributor to ICT enabled services. Adequate digital literacy aids widespread anytime access to e-health service (Alam, 2018). Aziz (2020) in his exploratory research conducted on the National ICT Policy of Bangladesh published in 2015 identified that even though policy focuses mainly on infrastructural development across the country by making rapid ICT network expansion and services, but it lacks sufficient detail on its realization. There is hardly any action plan towards its goal of affordable accessibility of ICT infrastructure, particularly in rural areas of Bangladesh. It is important to provide specific guidelines on how communities will overcome socio economic challenges to access ICT resources and contribute to the increase of digital literacy. Even though Bangladesh government has established task force for digitizing the education at national level, but accessible guidelines and clear mechanisms are important factors to ensure its real impact. In Bangladesh, there is an awareness of digitization need for augmenting education quality, equity, and efficiency at the national level. However, low digital literacy has been a constraint in realizing this awareness intro reality (Lim et al. 2020). It has been also evident in research that in countries like Bangladesh, digital literacy can contribute significantly to bridge the digital divide (Islam & Inan, 2021).

1.2 Problem Statement

In the current digital era, the concept of Digital Supply Chain (DSC) has gained significant momentum and widespread acceptance across various industries, predominantly in the manufacturing sector (Frederico, 2021; Ageron et al., 2020). Yet, this digitization surge's influence on service-oriented knowledge-based institutions like Higher Education Institutions (HEIs) is a sphere that remains relatively under-explored, particularly in least developed countries like Bangladesh.

In this context, one of the most significant barriers to the successful implementation of DSC practices in HEIs is the lack of a comprehensive understanding of the factors influencing these practices. The role of stakeholders, their acceptance, and their adaptation of technological innovations is a field that remains largely under-researched (Passey et al., 2016). This gap in the existing literature indicates a pressing need for studies exploring the factors that shape stakeholders' intention to use DSC practices.

One such influential factor is the concept of digital literacy, which encompasses the skills, competencies, and attitudes that enable individuals to effectively utilize digital tools and technologies. Prior research indicates the impactful role digital literacy plays in the adoption and efficient use of digital technologies (Van Deursen & Van Dijk, 2019; Bawack & Kamdjoug, 2018). However, an examination of how digital literacy potentially impacts the adoption of DSC practices in HEIs, particularly in less developed countries, remains largely absent in existing literature.

The environment in which these digital tools are used is also critical. This refers to facilitating conditions that include infrastructure, resources, and support available to stakeholders, enabling them to use digital technologies. Existing research points towards the importance of such conditions in the acceptance and efficient use of technology (Zhang et al., 2022; Wu and Zhang, 2018). Yet, an exploration of how these facilitating conditions shape the adoption of DSC practices within HEIs is scarce.

Perceived facilitating value, a relatively recent construct in the academic discourse, is another factor this study seeks to explore. It speaks to the perceived benefits and advantages of using digital technologies. While the importance of perceived value in technology acceptance has been noted in numerous studies (Chang et al., 2019, Eneizan et al., 2019), an exploration of its influence on inclination toward DSC within the confines of HEIs remains under-researched.

Performance expectancy is another area under consideration in this study. This construct is concerned with stakeholders' belief that employing DSC practices will lead to enhanced job performance. Although identified as a significant determinant of technology acceptance in various studies (Eneizan et al., 2019; Kwateng et al., 2019), the influence of performance expectancy on the inclination towards DSC usage in HEIs is an area that warrants more academic attention.

Trust is a critical component in determining stakeholders' inclination to use digital technologies. Trust becomes especially relevant in the context of digital technologies, where data security and privacy often emerge as significant concerns (Jaradat et al., 2020, Almaiah et al., 2019). Despite its importance, the role of trust in influencing stakeholders' inclination towards DSC usage in HEIs has not been sufficiently addressed in the existing literature.

While the study takes into account these potential influencing factors, it also pays close attention to the extent of the actual practice of DSC among HEI stakeholders in Bangladesh. The relationship between the influencing factors and the extent of DSC implementation remains unexplored within the academic landscape. This study seeks to illuminate this aspect, thereby filling an important theoretical gap in the literature. By doing so, this investigation aims to provide valuable insights that can inform strategies promoting the adoption and usage of DSC practices within HEIs, particularly in less developed countries like Bangladesh. Ultimately, this study seeks to contribute to the academic discourse on digital advancement within HEIs, improving the quality of education and research in Bangladesh and similar regions.

The proposed study intends to address this gap by focusing on the key independent variables - digital literacy (DL), facilitating conditions (FC), facilitating value (FV), performance expectancy (PE), and trust (T) - and their influence on the dependent variable, the stakeholders' DSC usage intentions. Understanding these factors is crucial, as stakeholders' intention to use DSC practices is believed to have a significant impact on the actual implementation of these practices.

Moreover, the relationship between these factors and the actual DSC practices remains unclear and largely untested. This indicates a significant theoretical gap in the existing literature, which the proposed study seeks to address. By exploring this relationship, the study aims to provide empirical evidence on how stakeholders' DSC usage intentions mediate the implementation of DSC practices in HEIs in Bangladesh.

Existing research on DSC practices in HEIs has predominantly focused on developed countries, offering models and frameworks that may not be entirely applicable or effective in the context of least developed countries like Bangladesh (Rahman et al., 2019; Munir et al., 2017). The differences in the economic, social, and infrastructural conditions between these countries suggest the need for a more flexible and adaptable DSC model that takes into account the unique circumstances and limitations of least developed countries.

In addition to this, the data regarding Bangladesh's digitalization status is sporadic and non-specific, making it challenging to evaluate the digital development of HEIs independently and regularly. This lack of a standardized model hampers the HEIs' ability to align with the dynamic global technological environment (Sarker et al., 2019).

This lack of data not only restricts the ability of HEIs in Bangladesh to evaluate their digital progression accurately but also hampers their ability to align or adopt the trajectory of technological development consistently (Al-Zaman, 2020). The absence of a standardized model of factors to be considered when evaluating HEIs and their digital development separately hampers the HEIs' ability to evolve with the dynamic global technological environment (Sarker et al., 2019).

This necessitates a broader understanding of the DSC model's applicability, considering the unique constraints and conditions in the least developed countries. Given this context, the proposed study aims to explore a more generic, flexible, and adaptable DSC model that can accommodate the limitations of digitalization in countries like Bangladesh.

Thus, this study seeks to contribute to the literature by investigating the factors that influence the intention to use DSC practices among stakeholders in HEIs in Bangladesh and how these intentions mediate the actual implementation of these practices. By doing so, the study will provide a clearer understanding of the roles and impacts of DL, FC, FV, PE, and T on the DSC usage intentions and practices.

Furthermore, this study aims to address the gap in the literature by providing evidence on the applicability of a DSC model in the context of least developed countries. In doing so, the study will not only offer valuable insights into the specific challenges and needs of HEIs in Bangladesh but also contribute to the broader understanding of digital transformation in higher education in least developed countries.

The proposed study also seeks to explore the mediating role of stakeholders' DSC usage intentions in the relationship between the independent variables (DL, FC, FV, PE, T) and the implementation of DSC practices. This is a significant area that has remained largely unexplored in the existing literature, indicating a significant theoretical gap. By addressing this gap, the study will contribute to a more comprehensive understanding of the dynamics involved in the digital transformation of HEIs.

The theoretical and practical insights derived from this study are expected to contribute significantly to the literature on digital transformation in higher education, especially in the context of least developed countries like Bangladesh. The findings are also expected to provide valuable guidelines for policymakers and practitioners in the higher education sector, enabling them to effectively strategize and implement DSC practices in HEIs.

1.3 Research Questions

i. What are the factors that can prescribe the intention of Digital Supply Chain (DSC) usage among HEI stakeholders in Bangladesh?

   a. What is the effect of digital literacy on the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.

   b. What is the effect of facilitating conditions on the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.

   c. What is the effect of facilitating value on the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.

   d. What is the effect of performance expectancy on the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.

   e. What is the effect of trust on the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.

ii. How to analyze the association between the intention and practice of Digital Supply Chain (DSC) among HEI stakeholders in Bangladesh?

iii. How to measure the mediating effect of stakeholders' intention on the relationship between the factors and the practice of Digital Supply Chain (DSC) among Bangladesh's HEI stakeholders?

a. What is the mediating effect of Digital Supply Chain usage intention on the relationship between digital literacy and the Digital Supply Chain (DSC) practice among Bangladesh's HEI stakeholders?

b. What is the mediating effect of Digital Supply Chain usage intention on the relationship between facilitating conditions and the Digital Supply Chain (DSC) practice among Bangladesh's HEI stakeholders?

c. What is the mediating effect of Digital Supply Chain usage intention on the relationship between facilitating value and the Digital Supply Chain (DSC) practice among Bangladesh's HEI stakeholders?

d. What is the mediating effect of Digital Supply Chain usage intention on the relationship between performance expectancy and the Digital Supply Chain (DSC) practice among Bangladesh's HEI stakeholders?

e. What is the mediating effect of Digital Supply Chain usage intention on the relationship between trust and the Digital Supply Chain (DSC) practice among Bangladesh's HEI stakeholders?

1.4 Objectives of Research

The aim of this research is to develop a model of digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh, representing least developed countries. The specific objectives are:

i. To identify factors that can prescribe the intention of Digital Supply Chain (DSC) usage among the Bangladesh HEIs stakeholders.

ii. To analyze the association between the intention and practice of Digital Supply Chain (DSC) among the Bangladesh HEIs stakeholders.

iii. To examine the mediating effect of the Bangladesh HEIs stakeholders' intention on the relationship between the factors and the practice of Digital Supply Chain (DSC) among the Bangladesh HEIs stakeholders.

1.5 Scope of the Study

This study focuses on investigating the factors that influence Digital Supply Chain (DSC) practices in Higher Education Institutes (HEIs) of the Least Developed Countries, with a specific focus on Bangladesh, serving as a representative case. The challenges and limitations faced by HEIs in these countries, such as low human capital, economic constraints, and inadequate infrastructure, are taken into account. The research scope encompasses understanding the factors that influence DSC practices within the HEIs of Bangladesh's stakeholders, with a specific focus on the role of stakeholders' intention as a mediating factor. The study seeks to explore the perspectives and experiences of different stakeholder groups to gain a comprehensive understanding of the factors influencing DSC practices. The research scope extends to the application of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model as the underlying theoretical framework. The UTAUT2 model provides a comprehensive perspective on the determinants of technology acceptance and usage intention. By employing this model, the study aims to identify the factors that influence stakeholders' intention to adopt and utilize DSC practices in HEIs.

The unit of analysis in this study is the stakeholders from all Higher Education Institutes (HEIs) in Bangladesh. This includes university students, university teachers, and university administrators. The research population consists of stakeholders from HEIs in Bangladesh, which includes university students, university teachers, and university administrators. The overall population of HEI stakeholders in Bangladesh is approximately 1,308,569 (University Grants Commission of Bangladesh, 2020). A sample size of 434 stakeholders was selected for this study, representing a diverse range of stakeholders. Among the respondents, 82.49% were university students (358 respondents), 11.98% were university teachers (52 respondents), and 5.53% were university administrators (24 respondents). By considering the viewpoints of different stakeholders, the research aims to provide a comprehensive understanding of the factors influencing DSC practices and stakeholders' intention to adopt and utilize them. Geographically, the study participants were also distributed across different areas, including urban, suburban, and rural areas. The majority of the respondents, accounting for 77.65% (337 respondents), were from urban areas. Suburban areas accounted for 12.44% of the sample (54 respondents), while rural areas had the lowest representation of only 9.91% (43 respondents).

Data analysis in this study is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), a statistical technique that allows for the examination of complex relationships among variables. PLS-SEM provides a robust method for analyzing the relationships between the identified factors, stakeholders' intention, and DSC practices. The findings of this study have implications for policymakers and practitioners in the higher education sector, providing valuable insights into how to enhance digital supply chain practices and improve the overall operational efficiency and effectiveness of HEIs.

1.6 Significance of the Study

The significance of this study is multilayered and stems from both its contribution to the existing body of academic knowledge and its practical implications within the domain of Higher Education Institutions (HEIs), particularly in less developed countries like Bangladesh.

From an academic standpoint, this study fills crucial gaps in the extant literature. Primarily, it extends the discourse around digital supply chain (DSC) practices beyond the manufacturing industry and into service-oriented, knowledge-based institutions such as HEIs. This is particularly important given the increasing role that digitalization plays in education and the potential for DSC practices to enhance efficiency within this sector.

Furthermore, by examining the impact of digital literacy, facilitating conditions, facilitating value, performance expectancy, and trust on the adoption and implementation of DSC practices, the study provides a deeper understanding of these constructs within the unique context of Bangladeshi HEIs. Each of these constructs has been widely studied within various contexts and industries, but their specific application and relevance to DSC practices within HEIs, especially in less developed regions, is not thoroughly understood. Therefore, this study enriches the academic discourse around these constructs and their impact on technology acceptance and usage.

Finally, this research bridges the gap between theory and practice by examining not just the intention to use DSC practices but the actual usage among HEI stakeholders in Bangladesh. This focus on practical application provides a more comprehensive view of technology acceptance and usage, addressing a major gap in existing research.

On a practical level, the study carries several significant implications. Firstly, by identifying and examining the key factors that influence the adoption and implementation of DSC practices within HEIs, the study can provide valuable insights for policy-makers, educators, and administrators within the education sector. These insights can help them devise strategies and interventions to enhance the adoption and effective use of DSC practices, ultimately leading to more efficient and effective educational institutions.

Secondly, the study's findings can provide a roadmap for other less developed countries seeking to enhance digitalization within their HEIs. By examining the unique challenges and factors that impact technology acceptance and usage within Bangladesh's HEIs, the study can offer valuable lessons for other similar contexts.

Overall, this study represents a significant contribution to the academic discourse around digitalization within HEIs and carries substantial practical implications for educators, administrators, policy-makers, and other stakeholders within the education sector.

1.7 Operational Definition of Key Terms

Digital Literacy (DL): Digital literacy represents the capacity to understand, access, integrate, manage, evaluate, create, and communicate information securely and correctly using digital technologies for entrepreneurship and employment (UNESCO, 2018). Digital Literacy within this study refers to the ability of HEI stakeholders (e.g., students, faculty, administrators) to effectively and critically navigate, evaluate, and create information using a range of digital technologies.

Facilitating Conditions (FC): Facilitating Condition, "the degree to which an individual believes that an organization's technical infrastructure is in place to support the use of the new technology" (Venkatesh et al., 2003). The notion that the environment, comprising of the IT support and infrastructure, is made more 'user-friendly' so as to make work easier (Bervell & Arkorful, 2020; Vairetti et al., 2019). Facilitating Conditions, in this study, encompass the degree to which stakeholders believe that an organizational and technical infrastructure exists to support the use of DSC practices.

Facilitating Value (FV): Facilitating Value refers to the perceived benefits that stakeholders perceive they will receive by adopting DSC practices. Studies suggest that perceived value is a critical factor that influences the intention and adoption of new technologies (Venkatesh et al., 2012; Wu and Zhang, 2018). Facilitating Value, in the context of this study, refers to stakeholders' perception of the advantages and benefits that using DSC practices could bring to their academic or administrative tasks.

Performance Expectancy (PE): Performance Expectancy, defined as "the degree to which an individual considers that using a technological system will help improve job performance", can be increase convenience, efficiency, accessibility, customization, as well as save on time and effort, achieved by using and adopting technology (Alalwan et al., 2018). In this study Performance Expectancy refers to the degree to which a stakeholder believes that using DSC practices will help them attain gains in job performance.

Trust (T): Trust refers to the belief that stakeholders have in the reliability, security, and privacy of the technology and the provider. (Jaradat et al., 2020, Almaiah et al., 2019) Trust, in the context of this study, pertains to the stakeholders' belief in the reliability and integrity of the digital technologies used in DSC practices.

Digital Supply Chain (DSC) Usage Intention: Usage intention focuses on the likelihood that users will continue using the technology, contingent on the various constructs. It explores the conscious patterns of a user's behavior with a planned intent, measured by the conative loyalty (Alalwan et al., 2018). Usage Intention, as defined in this study, is the degree to which a stakeholder plans to use DSC practices in their academic or administrative activities.

Digital Supply Chain (DSC) practices: Digitization practice refers to the actual use of digital supply chain practices in higher education institutions (Nikou & Aavakare 2021, Aavakare, M., 2019). Within the context of this study, DSC practices refer to the use of digital technologies, including information and communication technologies

(ICT), to manage and coordinate the various activities involved in the delivery of educational services within Higher Education Institutions (HEIs).

1.8 Outline of Thesis

Overall, this thesis consists of five chapters, and the description of each chapter is as follows.

Chapter 1 introduced the fundamentals of digitizing the academic supply chain in terms of stakeholders' intention and adoption. The discussion leads to constructing the problem statement and determining the objectives that need to be achieved by this research. Chapter 2 explores academic supply chain studies, the digitization situation of LDCs and their HEIs, and a contemporary technology acceptance model. Eventually, a conceptual research framework is developed by combining the factors as presented in the existing model and other significant factors as explored and identified from the relevant literature. The research framework focuses on the factors that influence the digital supply chain (DSC) usage intention among the stakeholders of HEIs in LDCs and also further identifies their DSC practice adoption. The relevant hypotheses are also presented in this chapter.

In Chapter 3, the methodology of analyzing and evaluating the model of factors focusing on DSC usage intention and practice adoption is elaborated. Initially, the plan of analyzing the factors through an exploratory method is presented. Later, the detailed process of how the correlation among the factors towards DSC usage intention and, eventually, DSC practice adoption among the HEI stakeholders of LDCs would be assessed is presented. Chapter 4, as per the methodology presented in Chapter 3, presents the data analyses step by step. The factors' correlations are observed with data in this chapter, along with the mediation impact of DSC usage intention on these factors toward DSC practice adoption among the HEI stakeholders. The model of these factors and their correlations are eventually tested, and relevant data analysis is presented in this chapter. Chapter 5 summarizes the contributions of the DSC model, highlighting some of the limitations and strategic recommendations/suggestions for the model in the long run.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides literature related to digitization in Supply Chain Management (SCM) and the application of SCM in Higher Education Institutes (HEIs) and has been organized into seven main parts. Section 2.2 presents a summary of the literature on Digital Supply Chain (DSC), and Section 2.3 provides studies conducted on the application of Supply Chain Management in the HEIs. Digitization in Bangladesh and their HEIs is discussed in Section 2.4 and digital literacy in Bangladesh is presented in Section 2.5. Section 2.6 illustrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model as one of the key underpinning theories of this study, and a summary and the gap are presented in Section 2.7. A conceptual framework model of Digital Supply Chain practice is designed in Section 2.8. Finally, the adopted methodology of this study, Partial Least Squares Structural Equation Modeling (PLS-SEM), is presented in Section 2.9.

2.2 Digital Supply Chain

Supply chains, just like the businesses they connect, will be rendered outdated and incur losses, if they fail to embrace and integrate technological innovations into the long-established value chains on time (Menon & Shah, 2019). It is just a matter of time that all the traditional supply chain management will gradually shift to digitization. The adoption of digitized technologies is in the process and a good number of companies have already taken steps to transform and redesign their business processes in this line (Aćimović & Stajić, 2019). Even though numerous researchers and corporates are working in the Digital Supply Chain domain, it is a continuous and rigorous process and widespread practical adoption will require time. A study of Accenture reported that just 28% transport and logistics companies rated themselves 'advanced' on digitization (Brightmore, 2021). In general, digitalization begins when there was a diffusion of technologies in terms of internet-based information and communication since the years of 2000 (Bicocchi et al., 2019).

Digital supply chain (DSC) is made up by systems such as communication networks, hardware and software that helps to organize a series of supply chains' activities for instance procurement, manufacturing, storing, transferring, and selling the products (Aćimović & Stajić, 2019). Cecere (2016) added that it is able to work bi-directionally from market to market. Besides, to create new opportunities in the supply chain sector, a different perspective is required. The flow of products and services, as well as information should be shared across the extended enterprise. This information flow creates unforeseen values for all stakeholders of the supply chain. In this regard, digitalization tends to provide more valuable, accessible, affordable services that brings effective, agile, and consistent outcomes (Büyüközkan & Göçer, 2018; Kinnet, 2015).

According to Chauhan and Singh (2019), digitalization was also highlighted in the context of Industry 4.0 implementation. In Industry 4.0, every part of company is said to be digitalized and automated (Trstenjak & Cosic, 2017). It employs the future-oriented technologies, principles of cyber-physical system (CPs) and other smart systems which enhances human interaction with the machine (Longo et al., 2017; Sanders et al., 2016). It involves the products and services, flexibly connected via internet or various other network application (Hofmann & Rusch, 2017). Industry 4.0

is a platform where all participants are attached and exchange information with each other (Tjahjono et al., 2017; Schlechtendahl et al., 2015). Xu et al. (2018) expressed that Industry 4.0 highly depends on data acquiring and sharing through interconnected business services, processes, and information systems. With digitalization, performance in terms of productivity, energy efficiency, cost, and security has the potential to improve as real-time system communication and cooperation are allowed (Peruzzini et al., 2017). Digital Supply Chain Institute devised the DSC Execution Framework as Figure 2.1 (Digital Supply Chain Institute, n.d.), which consists of four main components: demand, technology, people, and risk.

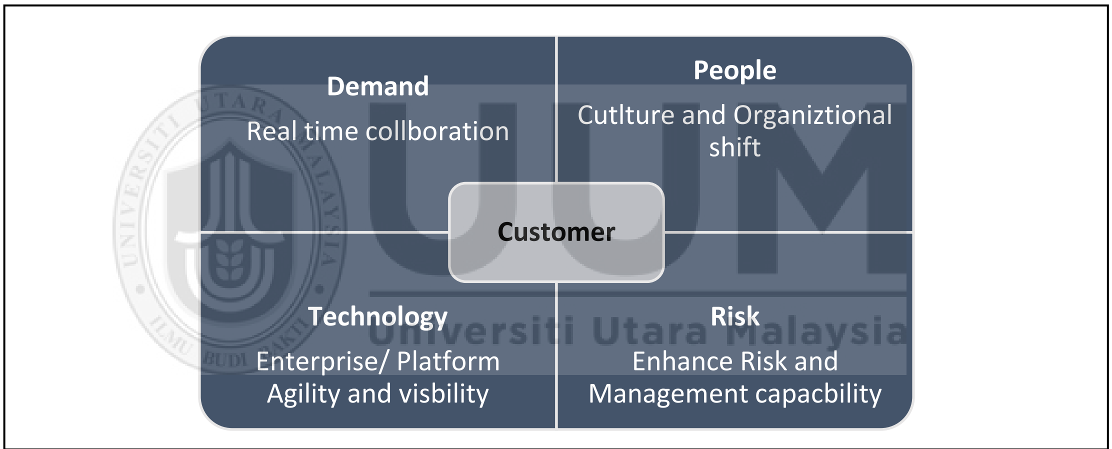

Figure 2.1. DSC Execution Framework (*Source:* Digital Supply Chain Institute, n.d.)

DSC has been introduced widely in many industries. A previous study by Patrucco et al. (2020), which focuses on DSC application in construction industry, explored how the use of Industry 4.0 technologies could provide better support in managing the processes of supply chain. According to the study, it was focused on the process of receiving incoming materials and supporting outgoing materials. The adoption of Industry 4.0 technologies, such as cloud manufacturing, Internet of Things (IoT) and smart tracking sensors could help to solve the critical issues such as absence of planning and standardized procedures, complexities of coordination and communication among key actors, and inefficient automation activities (Patrucco et al., 2020). Besides that, DSC is also applied in food supply chain, studied by Kittipanya-Ngam and Tan (2020), which explores the tasks and difficulties towards digitalization of food supply chain and production procedures in Thailand. The application of DSC in the food industry becomes imperative because of the issue of product perishability, need of requirement traceability, and the urgency to improve productivity due to its low margin.

2.2.1 Attributes and Characteristics of Digital Supply Chain

There are some attributes related to DSC being focused on this study, such as supply chain structure, agility, visibility and also automation. In terms of supply chain structure, a linear supply chain is not applicable anymore. The ideal supply chain is generally comprised of certain characteristics, for instance shorter path lengths, high clustering coefficient, and scale-free. In other words, the ideal supply chain is a network clustered around the center around the firm in managing its supply chain (Min et al., 2019; Hearnshaw & Wilson, 2013). With a central platform, the information exchange can be done through clouds to make the supply chain flexible and combine of various possible configurations (Zhang et al., 2019; Cegielski et al., 2012).

Next, visibility in supply chain can be achieved by sharing relevant data as it aligns processes and activities of the supply chain for a convergence understanding (Somapa et al., 2018; Chengalur-Smith et al., 2012). A high level of visibility would be useful for companies to efficiently manage and optimize their supply chain processes by adopting interactive dashboard, on-demand reports, and other well-structured outputs (Parviainen et al., 2017). Meanwhile, agility is also necessary to deal with unexpected disruptions, enhance quality and tackle risks (Braunscheidel & Suresh, 2018). In addition, automation is one of the attributes in DSC. Automation in physical and planning processes usually significantly contributes to proper utilization of resources, minimizing waste and faster operational processing. (Manavalan & Jayakrishna, 2019; Alicke et al., 2016).

With the wave of Industry 4.0, its technological applications on traditional supply chains can be traced by six value drivers – planning, physical flow, performance management, order management, collaboration, and supply strategy, which subsequently establishes the benchmarks of practices in services, cost, capital, and agility of SCM. Some of the major trends in SCM influence these six value drivers in the course of the digitalization of supply chains today.

One of the common value drivers is Big Data (BD) (Haddud & Khare, 2020; Menon & Shah, 2019; Büyüközkan & Göçer, 2018). Previous research from Haddud and Khare (2020) claimed that BD is the second most influential technology. BD refers to any huge amount of structured or semi-structured, or even unstructured data that has the potential to store valuable information (Patrucco et al., 2020). It involves the use of artificial intelligence and machine learning techniques to extract and process information from widespread datasets for modeling and forecasting (Ardito et al., 2019; Kang et al., 2016). It supports in decision making by revealing correlations, patterns and future directions, and other valuable information and intelligence, which helps to boost profitability, increase process efficiency, and discover opportunities and potential markets (Tiwari et al., 2018).

The next driver of DSC is cloud computing (CC) (Patrucco et al., 2020; Zhang et al., 2019; Büyüközkan & Göçer, 2018). CC provides a virtual service through the network, and thus, users can access the information anytime and without matter the location (Menon & Shah, 2019). This is because the application of CC could keep the inventory information update in real-time without the need for users to wait for centralized update of information all over the supply nodes (Hartley & Sawaya, 2019). Disha and Parekh (2013) added that CC is the service that could instantly be ready with the least amount of organizational effort.

Internet of Things (IoT) is also one of the common drivers in digitalization (Patrucco et al., 2020; Menon & Shah, 2019; Zhang et al., 2019; Büyüközkan & Göçer, 2018). IoT refers to the daily elements that comprised of internet connectivity so that they can communicate to transfer data amongst themselves, other systems, or devices (Ben-Daya et al., 2019). According to Zhang et al. (2019), the association of IoT and supply chain can enhance the traceability and benefit the food and cold chain manufacturing industry. This is because supply chain operations can be better managed remotely using IoT and eventually leading to efficient decision making is presence of precise information (Ben-Daya et al., 2019). A summary of some popular DSC enablers found in various research is tabulated in Table 2.1.

Table 2.1

Digital Supply Chain Enablers

DSC Enabler	**Impact on SCM**	**Author (year)**
Big Data (BD)	Retrieve and process information from widespread sources of data for modeling and forecasting	Haddud and Khare (2020), Patrucco et al. (2020), Menon and Shah (2019)

Table 2.1 continued

DSC Enabler	Impact on SCM	Author (year)
Cloud computing	Flexibility of supply chain, variety of possible configurations and traceability and facilitating Collaboration for SCM	Patrucco et al. (2020), Menon and Shah (2019), Zhang et al. (2019), Büyüközkan and Göçer (2018), Disha and Parekh (2013), Cegielski et al. (2012)
Machine learning	Consolidate to determine the anomalies in the process for Performance Management	Büyüközkan and Göçer (2018), Ardito et al. (2019), Kang et al. (2016)
Internet of Things (IoT)	Exchange data, and communicate among objects and other network devices and systems	Patrucco et al. (2020), Ben-Daya et al. (2019), Menon and Shah, (2019), Zhang et al. (2019), Büyüközkan and Göçer (2018)
3D printing/additive manufacturing	Represents connected and agile prototyping of parts of products, enabling customization and streamlining the physical flow	Shree et al. (2020), de Sousa Jabbour et al. (2018)
Augmented reality/ virtual reality/mixed reality and robotics	Enhancing business processes, increasing operational efficiencies, and leveraging overall competitiveness.	Rejeb et al. (2021)
Block chain	Improve SCM transparency, traceability, and auditability	Zhang and Sakurai (2020), Song et al. (2019)

Even though most of the DSC enablers mentioned in the above table were researched for the manufacturing and service industry, some of these can be integral part of Digital

Supply Chain for Higher Education Institutes. The HEI stakeholders' intention of using them and adopting them in the DSC practice is one of the prime objectives of this research.

2.2.2 Benefits of Digital Supply Chain

Previous studies have identified several benefits of having digital supply chain (DSC) in an organization. One of them is cost control, which can be achieved through combining and exchanging information. This can be done by using the IoT devices and CC server which can help to reduce time and cost spent on communicating circulation (Zhang et al., 2019). The next benefit of DSC is traceability which is a prime attribute of an efficient supply chain as it helps to track the status and condition of the product in real-time. This helps supply chain managers to make faster decisions and coordinate flexible plans. Another benefit of high-efficient traceability is the low-cost management of the transportation network in the supply chain (Zhang et al., 2019).

Besides that, transparency is also one of the benefits of DSC. Transparency refers to the capability to identify some useful information, for instance, the way to act and manage timing as well as locations. Real-time inspection and auditing of supply chain data for highly visible activities and operations are enabled by true transparency (Abeyratne & Monfared, 2016). As an example, Lewis (2017) expressed that traceability and transparency could verify the upstream information in the food supply chain and make the information easily available regarding the materials, their sources, suppliers, as well as the steps of processes that the materials went through. The traceability and transparency provide benefits to end users in the context of trust and safety (Gharehgozli et al. 2017).

Accountability is also one of the benefits of DSC. With a feature of accountability, it is able to trace back the responsible members or processes whenever there are some unexpected incidents by analyzing the recorded activities. The evidence seems to be much imperative for problem solving (Zhang et al., 2019). For instance, a food supply chain that exports the products to countries in which the consumers are highly concerned about environmental and social issues will expose to a stricter set of rules and regulations. The legal requirements which are getting stricter could only be supported by ever-improving digitalization (Kittipanya-Ngam & Tan, 2020).

Speed, flexibility, and global accessibility are just some of the basic benefits of digitalizing the academic supply chain. The efforts to address the implementation of a DSC appear to be scattered across its various aspects of IoT, Cloud Computing, Big Data, etc., with its respective literature seemingly indeterminate and unstructured. Based on the available research on digital supply chain management, its apparent that most of the literature are qualitative and narrative-based, focusing on a particular segment of the entire digitalization of SCM, with minimal emphasis given to the uncharted area of SCM like academic institutions (Seyedghorban et al., 2020).

DSC also plays an important role in technology transfer. Technology transfer refers to the process of technology distribution and retention within different cultures. It involves the exchange of applicable knowledge, result of implementation and product being produced among two persons or industries involved (da Silva et al., 2019) as illustrated in Figure 2.2. The technology basically comprised of two phases which are the donor and the recipient. The donor has the responsibility to share technologies while the recipient should be able to adopt the technologies shared (Miranda et al., 2017).

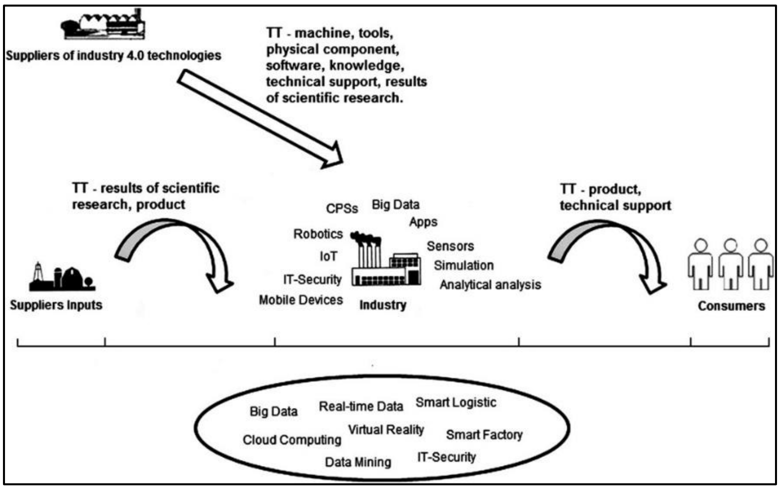

Figure 2.2. The processes within major stages of Digital Supply Chain (*Source:* da Silva et al., 2019)

According to Büyüközkan and Göçer (2018), the digital transformation that are connected to Industry 4.0 are about to enhance the business model and organization. In this regard, previous research has focused on sharing of information and making decisions throughout the supply chain as a result of digitalization (Preindl et al., 2020). Digitalization which involved information sharing has resulted in much higher amount of data accumulation and utilized by decision maker (Dunke et al., 2018). Satisfying customer requirements is a common objective achieved from better decision making and real-time interpretation of data (Govindan et al., 2018). Dweekat et al. (2017) added that the collected data can be analyzed and organized to generate a decision support system which can contribute to coherence, consistent and efficient decisions. Recently, the transformation in supply chain allows new electronic traceability systems to track inventory, sales and purchases which are useful for companies. A smart supply chain is introduced to create quality information which consists of characteristics such as correctness, timeliness, frequency, improved quality, as well as security (Wu et al., 2016). This helps to reduce cost as real-time optimization and contribute to the rise of agility as well as faster pace of information flow credited to real-time resource tracking (Dweekat et al., 2017).

The World Economic Forum (2019) mentioned that digitalization has a huge potential to reduce the emissions from logistics by as much as 15% and helps in global economy decarbonized. Also, it is desired to enhance the supply chains along with the business performance with certain characteristics such as better visualization and enhanced traceability, agility to change, precise error detection and maintenance, efficient management of inventory, and high-level participation of supplier and customer (Haddud & Khare, 2020). This can help to improve supply chain flexibility and reduce the risks and costs involved in supply chain (Agrawal & Narain, 2018).

According to Büyüközkan and Göçer (2018), the organization with DSC is able to carry out extraordinary performance to fulfill the customers' satisfaction. The DSC is able to provide more accurate information about customer needs through demand sensing and up-to-date sales information, built with efficiency for quicker and easier access of true customers. Greater transparency would lead to better decision making. This is because the more the number of alternatives available, the better the supply chain management decision (Agrawal & Narain, 2018). da Silva et al. (2019) added that digitalization has resulted in efficient, more agile, and consumer-focused supply chain. The innovations and technologies have resulted in a proper way to share and handle information despite more complicated supply chain integration (Hartley & Sawaya, 2019; Lotfi et al., 2013). Besides, a previous study carried out by Moeuf et al. (2017) found that the digital technologies of Industry 4.0 has influenced the reduction of cost, production flexibility, productivity enhancement, optimization production process, quality improvement, and reduced product delivery time to reach the end customer.

A list of benefits of using DSC is summarized in Table 2.2. These benefits highlight the importance of adopting digital supply chain practices in the newer domains and higher education institutes are no different. Since the concept of supply chain management is already studied in the higher education institutes by various researchers, it is imperative that the study of digitization of the HEI supply chain management eventually would become an essential requirement which this study is particularly addressing.

Table 2.2

Advantages of Having DSC in the Organization as found in various research

Advantages of having DSC in Organization	**Author (year)**
Valuable, accessible, affordable services to bring consistent, agile and effective outcomes	Haddud and Khare (2020), Büyüközkan and Göçer (2018), Dweekat et al. (2017)
Leverages revenue and business value	Kinnet (2015)
Flexible connectivity	Hofmann and Rusch (2017)
Human-machine interaction	Longo et al. (2017), Sanders et al. (2016)

Table 2.2 continued

Advantages of having DSC in Organization	Author (year)
Improved productivity, security, energy efficiency, and cost reduction	Agrawal and Narain (2018), Peruzzini et al. (2017), Dweekat et al. (2017), Moeuf et al. (2017)
Increased traceability, information accuracy, improved quality, better timing, speed, and privacy	Moeuf et al. (2017), Gharehgozli et al. (2017), Lewis (2017), Wu et al. (2016)
Real-time optimization	Dweekat et al. (2017)
Higher amount of data accumulation utilized by the decision maker	Dunke et al. (2018), Dweekat et al. (2017)
Real-time support for higher customer satisfaction	Büyüközkan and Göçer (2018), Govindan et al. (2018)
Reduced carbon emissions from logistics	World Economic Forum (2016)
Better maintenance predictions	Haddud and Khare (2020)
Accurate error identification	Haddud and Khare (2020)
Better supplier and customer participation	Haddud and Khare (2020), Büyüközkan and Göçer (2018)
Risk reduction	Agrawal and Narain (2018)
Better supply chain management decision	Agrawal and Narain (2018), Moeuf et al. (2017)
Accountability	Kittipanya-Ngam and Tan (2020), Zhang et al. (2019)

While DSC has already been a reality in developed countries worldwide, it is still a novel concept in emerging nations, especially sectors that are constrained by limited resources, including education. Industries, both product and service, in developing countries are yet to adopt the applications and integrate them into their practices. It is essential to initiate and undergo the full process of the technology transfer, in order to be able to execute and establish a digitalized SCM system.

From the literature of numerous research, it is realized that majority of Digital Supply Chain studies are conducted in the manufacturing industry and some in service industry. But there is a lack of research conducted in the DSC practices in higher education institutes. The following section discusses the Supply Chain application in Higher Education Institutes along with scope of adopting digitization.

2.3 The Application of Supply Chain Management in Higher Educational Institutions

Not many Supply Chain Management (SCM) researches have been carried out to model the application of SCM for the higher educational sector. Nonetheless, there are a few studies conducted, which include Pathik et al., (2012b), Habib (2010), Lau (2007), and O'Brien and Kenneth (1996).

In 1996, the academic supply chain concept was coined by O'Brien and Kenneth adapting industry model in higher education institutes. They conducted a study among the employees and students at the University of Strathclyde. The idea was integrated in the decision-making process (O'Brien & Kenneth, 1996). Even though the concept did not contribute to any significant model, it remained as one of the early references of the academic supply chain. The early stage of enterprise scale information system was still in its conceptual level at that stage of time.

Consequently, at the University of Hong Kong, Lau (2007) carried out an extensive case study analysis aligning with the concept of education supply chain management. That study consisted of a survey on the university stakeholders, like, employees, suppliers, customers. Ultimately a supply chain model was strategized for that university segmented into two separate supply chains – one known as student supply chain (as illustrated in Figure 2.3) and the other one as research supply chain (as illustrated in Figure 2.4).

As evident in Figure 2.3, a student plays two roles in the supply chain. One as raw material and as well as the finished product. In the Research supply chain, as shown in Figure 2.4, research ideas were denoted as raw materials and research outcomes are denoted as the final products (Lau, 2007). The nature of this research was not adequate to be generalized and as a result a theoretical concept of the academic supply chain was not possible to be established. The findings of Lau's (2007) research were not specific enough to constitute as a standard abstract model.

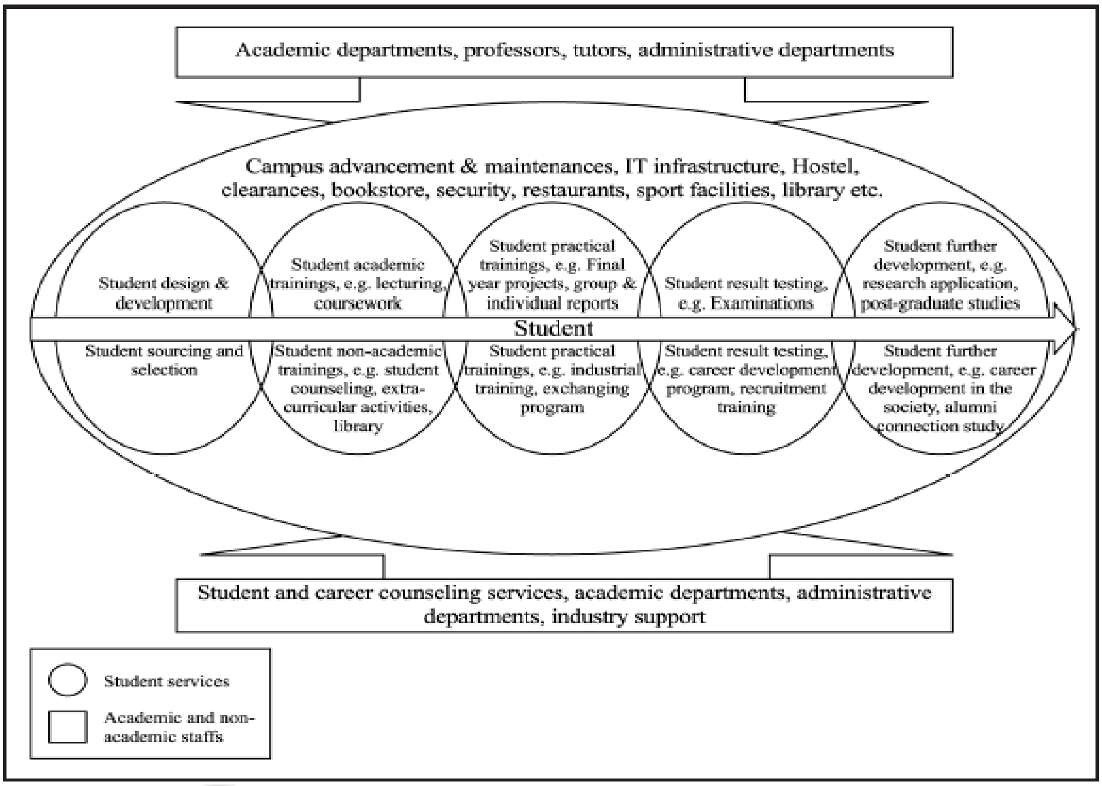

Figure 2.3. The "Student" SCM in the City University of Hong Kong (*Source:* Lau, 2007)

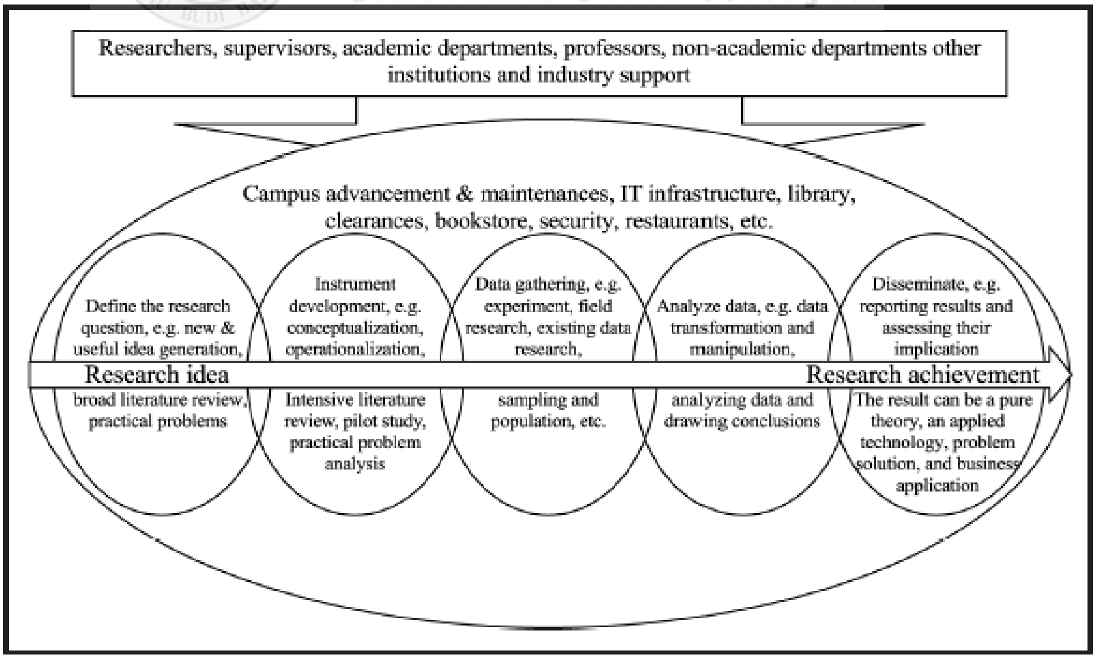

Figure 2.4. The "Research" SCM in the City University of Hong Kong (*Source:* Lau, 2007)

Based on tertiary educational institutes, a complete academic supply chain model named ITESCM (Integrated Tertiary Educational Supply Chain Management) was constructed by Habib (2010). Habib (2010a) explored responses from universities around the globe to construct this model. Almost 500 respondents' data were collected and analyzed. This academic SCM model combines management of education, supply chain for research and supply chain for education. Education and Research supply chains are independent of each other. The prime objective of the ITESCM model is to produce highly capable and skilled graduates, and highly impactful research. The administrators and investors of the higher education institutes will ensure fulfilment of these objectives by adopting the supply chain concepts. Th outcomes will eventually be beneficial for society (Habib et al., 2012a).

There are three decision layers - operational, planning, and strategic, combined with the education management in the ITESCM model. The education supply chain part of the model is a combination of these decision layers along with education management. It aims to conceptualize a novel model for effective learning supply chain management. The ultimate customer of ITESCM is society. Through the adoption of academic supply chain in the educational institutes ITESCM model wants to ensure enhancement of the society. A requirement of this model is to store updated information about all of its stakeholders in the chain, like, the consumers, service sources and service providers (Habib, 2014).

Later, a redesigned version of the ITESCM model was constructed by Pathik et al. (2012b, 2012c), which is apparently more user friendly, conceptual, and abstract. The model was constructed through empirical research, as shown in Figure 2.5. To apprehend its efficiency, the concept is supposed to be tested in well-established educational organizations of different categories. From Figure 2.5, four additional factors from Habib (2010) model are programs establishment (PE), faculty capabilities (FC), university culture (UC), and facilities (FA) (Pathik et al., 2012c). A summary of the four factors as follows:

i. Programs Establishment (PE): It is the initial task of every tertiary level institute. Every program needs to be developed and then assessed for its effectiveness and applicability. The learning starts after the Programs establishment (PE). Based on the diversity of the education development, every university designs and launches various degree programs for the students. For the diversification of assessment and development in research, universities need to introduce various degree programs. To support programs establishment, universities introduce innovative academic processes, placements for students in the industry, practical experience, IT facilities establishment, etc. (Pathik et al., 2012a).

ii. Faculty Capabilities (FC): In a university, faculty members create scopes and ensure students' participation in learning, feedback for curriculum enhancement, and innovative research. They create a rich learning atmosphere in the classrooms and engage students in effective communication. Generally, their faculty members are evaluated in three categories including services, teaching, and research (Pathik et al., 2012c).

iii. University Culture (UC): Habib (2010a) stated that like the personality of a human being there is also culture of a university. It is similar to the concept of organizational culture. University to university the culture differs based on the nature and objective of society, geographical location, and above all the management or administration of the university.

iv. Facilities (FA): One of the dynamic aspects of tertiary level education institute is the establishment of modern and latest facilities. Like, interactive engaging lecture environment using digital technology, digitalization of library facilities and global connectivity, state-of-the-art laboratories and their availability, campus-based IT services beyond classroom environment. These facilities offered to the students by the universities ensure an overall academic atmosphere where learning is spontaneous and enjoyable as well as effective. E-learning facilities in the classrooms through Internet, advanced online learning management system and real-time online education management administrative facilities are growing popular among universities globally. For research activities, facilities include easy access to online research repositories, like e-journal, e-books, authenticity tools, collaborative platforms, online repositories, modern well facilitated and equipped laboratories, etc. (Pathik et al., 2012c).

A complete review of Pathik et al. (2012b, 2012c) is depicted in Figure 2.5. Other research that used this model as their research model framework are Islam (2013) who applied the concept for a comparative study on three pubic and three private universities based on digital education model (Islam et al., 2013) and later, Hye (2014) also adopted that model in another comparative studies among two well-known private universities of Bangladesh.

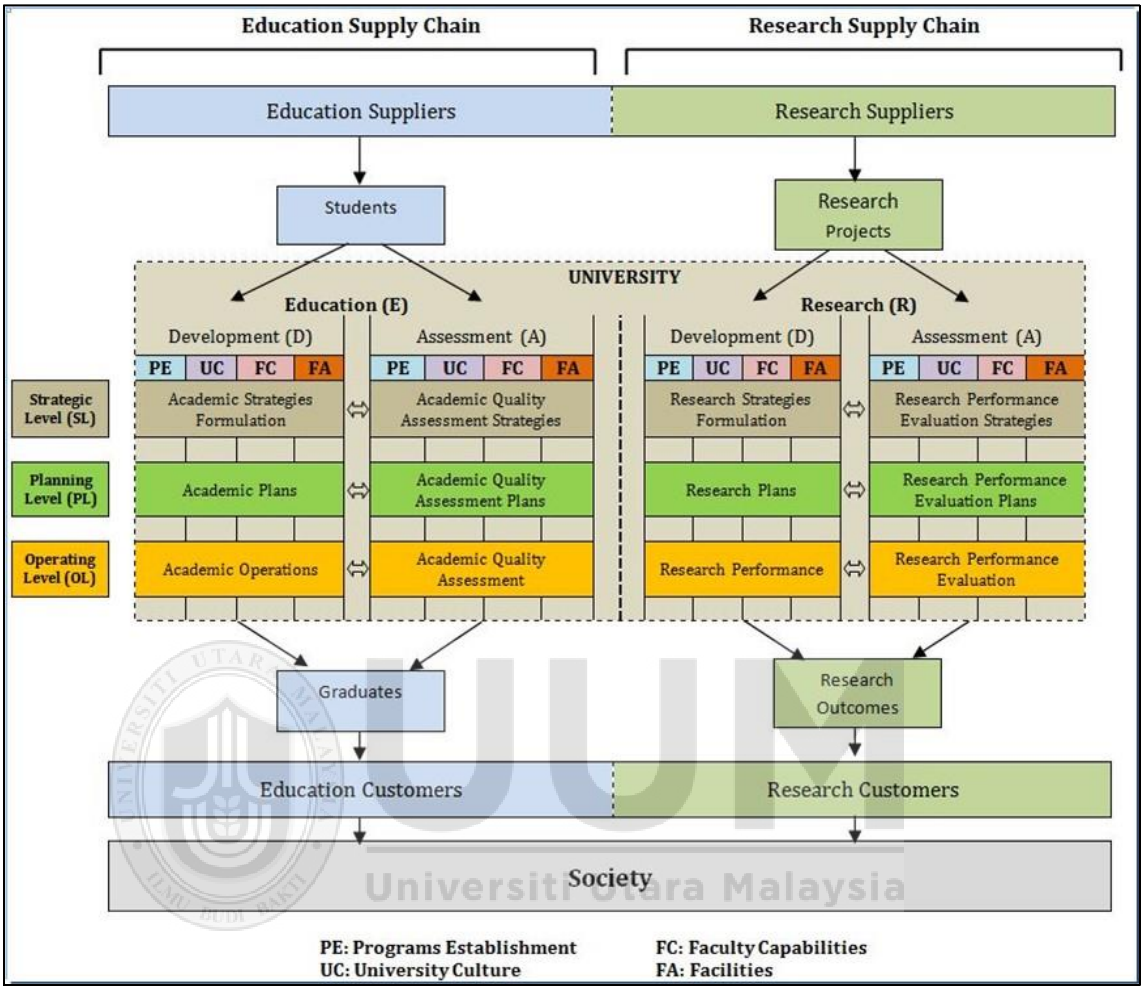

Figure 2.5. Redesigned ITESCM Model for the Universities (*Source:* Pathik, et al., 2012b)

A summary of supply chain management research works in the HEIs is presented in Table 2.3.

Table 2.3

Summary of the Studies on Supply Chain Management in HEIs

Author (year)	**Focus of Study**	**Supply Chain Performance Being Measured**	**Technique**
O'Brien and Kenneth (1996)	Using the industry model in higher education institutes. Students and employers of the University of Strathclyde were surveyed.	Integrating the idea into a decision-making process. Review of a department.	Review based on Survey of the stakeholders of a UG degree awarding department.
Lau (2007)	Case study-based research in the University of Hong Kong. Student SCM and Research SCM.	Student Employability and Research outcomes.	Interview based exploratory research.
Habib (2010)	ITESCM, a combination of supply chain for education and supply chain for research.	Quality Graduates and High Impact Research	Structural Equation Modeling (SEM) in AMOS
Pathik et al. (2012b, 2012c)	Facilities (FA), faculty capabilities (FE), university culture (UC) and programs establishment (PE)	Quality Graduates High Impact Research	Structural Equation Modeling (SEM) in AMOS

2.3.1 The Component of Supply Chain Management in Higher Education Institutions

Several researchers identified the components or entities for HEIs' supply chain from various perspective. Analogically, considering the basic supply chain model, one of the main 'inputs' of supply chain for HEIs are the students graduating from high schools and colleges who enroll in universities for higher education, who are then, in turn, 'processed' by the university faculty members and administrative staff (Pathik et al., 2012b, 2012c). Besides that, there vendors who supply the capital resources that enable the teaching-learning environment, for example, assets like the ICT equipment, classroom furniture and building infrastructure, along with those who supply the educational materials like the textbooks and stationery (Hye et al., 2014). This allocation of resources is made possible by those who ensure the financial supply in higher education – the students who pay their own tuition, parents/guardians who are the financial resource, as well as the private organizations, NGOs and government agencies, who provide funds through scholarships and grants in various capacities. Additionally, prior to the 'output' of the supply chain, as a part of the 'processing', research plays an important role. This research, conducted by faculty members as well as students, either independently or jointly together, tend to have two sources of financial supply (Pathik et al., 2012b, 2012c). Internally conducted research projects are usually self-funded by the universities themselves, while other research projects that address issues beyond the HEI are funded by external sources like private corporations, NGOs, government authorities (Habib, 2014).

Hye (2014) determined Customers into two categories, like, education customers of education and customer of research. Meanwhile, Islam et al. (2013) identified two categories of suppliers for higher education institutes, i.e., education suppliers and suppliers of research. From the perspective of flow of material or information in supply chain, students are recognized as raw materials in education chain, whereas external and internal research projects identified as raw materials for the research chain (Habib, 2014, Pathik et al., 2012b, 2012c, Habib, 2010).

The researcher of the education supply chain model identified two major activities. One is development and the other one is assessment, for both part of the model, education and research. Eventually, these development and assessment activities are formalized in four main activities- education development, research development, education assessment, and research assessment. Ultimately, the ITESCM model is structured as education supply chain model for the universities covering four aspects of the institution, including faculty capabilities, programs establishment, university culture, and facilities, and with the above mentioned four activities of development and assessment (Habib, 2014, Pathik et al., 2012b, 2012c, Habib, 2010).

The final outcomes of ITESCM are graduates and research as finished products which are delivered to the ultimate customer; the society (Habib, 2014). Hye et al. (2014) also agreed with Habib (2014) whereas a part of the supply chain, the ‘output’ of the education system are its graduates, who are also the customers, along with their parents/guardians. Employers of private companies and government organizations are also customers of higher education. On the other hand, in case of the research conducted by HEIs as a part of the ‘processing’, the customers tend to be organizations who fund the projects, with beneficiaries of the outcome of the research ranging through the numerous publications, the researchers, the target population, etc. Professional research organizations like IEEE, ACM, INFORMS, IEOM, SoME, etc. may also be the customers of the said research projects. All these customers are availing a service, in one way or another, in exchange of which there is a transaction taking place, that creates, adds, and returns value for the ‘product’, in this case a service of higher education.

Graduates with desirable quality delivered to the society is one of the final outcomes of the academic supply chain management along with identifying the value addition in the process of the university to generate quality graduates. The assessment of quality graduates includes moral, expertise, aptitudes, tacit and explicit knowledge, proficiencies, supported by graduate’s value addition, professional enrichment programs, modern ICT facilities, engagement in research, scholarship, etc. (Habib, 2014, Pathik et al., 2012b, 2012c).

Universities come up with strategic tactical plans for multi-disciplinary research to make sure the stakeholders are engaged in innovative activities and preserve its importance. Research outcomes may include theory development, solving problems, publications of findings, dissertation, projects proposals, applied research, etc. Research with higher impact is also a final outcome of academic supply chain management (Hye et al., 2014, Habib, 2014). The summary of node or entities and material/information flow that are consisting in supply chain structure of HEIs is shown in Table 2.4.

Table 2.4

Components and flow of Supply chain structure of HEIs

Flow of SCM	**Components**	**Author (year)**
Input	Students graduating from high schools and colleges Educational materials Financial supply Internal and external research projects	Habib (2014), Islam et al. (2013)
Process	Education development, education assessments, research developments and research assessments Programs establishment, university cultures, faculty capabilities and facilities	Habib (2014), Pathik et al. (2012b, 2012c)
Output	Graduates and research	Hye et al. (2014), Habib (2014)
Customer	Education customers and research customers Parents/guardians Government and privatized organizations Professional research organizations Society	Hye et al. (2014), Habib (2014), Pathik et al. (2012b, 2012c)
Performance Measurement	Quality Graduates High impact Research outcomes	Hye et al. (2014), Habib (2014), Pathik et al. (2012b, 2012c)

A supply chain management system consists of input, processing and output. For HEIs the input, processing, output, recipient customer and the efficiency of the supply chain were defined by the previous researchers as evident in table 2.4. These are the elements, digitization of which this study is exploring in terms of the HEI stakeholders' acceptance point of view.

2.3.2 Digital Supply Chain Practices in Higher Education Institutions

Higher Education Institutions (HEIs) deal with the same kind of operational challenges as any other business organization, considering the value chain that integrates key elements together in order to transform freshmen students into holistic graduates. The pedagogical system of teaching and learning is an alternate paradigm with new constructs that develop the educational model for supply chain management (Basu et al., 2016). The digitization of the education system altogether is considered to be both disruptive and enabling for teachers and learners alike – today, an increased level of digital literacy is demanded and expected from both (Chan et al., 2017; Alexander et al., 2017; Elgazzar & Elzarka, 2017). As an academic SCM, HEIs work closely with its stakeholders, including schools and colleges, along with its current students and staff, as well as the business organizations (Basu et al., 2016). Together as the major value chain, they collaborate on designing the curriculum, while developing the incoming students with the knowledge, skills, and attitude (KSA) in order to become skilled human resources to enter the job market in the future (Gopalakrishnan, 2015).

The difference being, now, not only is the entire process becoming more and more digitized, but even the implications to follow as well. Although web-based learning management systems (LMS) enabled online learning since 1995, it was not until 2008, when the first massive open online course (MOOC) broke into the scene of digital education as a platform for not only uploading and organizing learning content, but delivering it as well (Bates, 2015). This created highly interactive and constructive learning environments that unlocked a new gateway to rendering education far more accessible as well as affordable for a significant segment of the population. The scalable system allowed anyone to undertake courses whenever they want, from wherever they want, debunking the myth that education only takes place in a classroom setting up to a certain age. Despite the reality that 'everything cannot be taught online', digital education definitely untethers prospects for evolving the entire teaching-learning module in place today (Zawacki-Richter et. al, 2020).

From the general administration to the education administration, to pedagogical systems, the entire educational structure has been overhauled from manual to analog to digital. All the administrative functions required for an HEIs to operate, including human resource management, accounting, marketing, and customer service, along with the academic aspects of running a university from managing student applications, registration, organizing teaching assignments, grading, etc. have been digitalized into streamlined processes that can all be easily accessed and operated online (Chaushi et al., 2018). Slowly but surely, even pedagogical elements like curriculum design and development, monitoring and evaluation of teaching and learning, as well as assessment and evaluation of student progress, will soon become more and more integrated to digital supply chain in HEIs. Based on the 'lean thinking model', developed by Taiichi Ohno, the Chief Engineer of the Toyota Production System, just like in manufacturing, the educational system also incurs 'wastes' that can be eradicated by digitizing the academic supply chain, as illustrated in Table 2.5. The underlying principle when implemented into classrooms, have proven to be effective as 'agile classrooms', and shows great potential in doing just the same in digital academic SCM (Morien, 2019).

Table 2.5

Wastes of Education

Type of waste	Explanation
Overproduction	Irrelevant and unused curriculum and knowledge which is not usable.
Waiting	Students' knowledge that eventually turn out to be irrelevant by the time they graduate
Transport	Movement of learning material from one course to another causes that student need to re-learn. Even the physical distance of teaching location contributes to waste of time.
Inappropriate processing	Learning and assessment process that is not relevant to the topic or the curriculum as a whole. Continuation of Primitive techniques.
Inventory	Student memory stores the knowledge for future which sometimes becomes forgotten (compared to leakage in Lean Supply Chain Management terms)

Table 2.5 continued

Type of waste	Explanation
Unnecessary and excessive motion	Intellectual and physical movement of faculty members and students between courses and classes, high dependence on past knowledge, limitation of coherence in curriculum results in waste of motion
Defects	Unethical practices, like, cheating, plagiarism or lack of depth in learning, failure to see relevance of subject-matter, irrelevant of obsolete curriculum
Recognition of staff	Inability to acknowledge and identify faculty members' and students' capabilities and feedbacks, inability to develop or utilize substantial knowledge or research

Source: Morien, 2019

The literature review conducted on the supply chain management studies in higher education institutes, the stakeholders and their assessment of key processes are identified for this research. The stakeholders are the main focal points of data collection in this research. The SCM operations and performance measurements are also conceptualized in the research framework. The literature also reflects the lack of studies conducted on the Digital Supply Chain practices in the higher education institutes. Few studies that were explored are highlighted in this section along with the possibility of adoption in this research.

2.4 Least Developed Countries

According to the United Nations, "least developed countries" (LDCs) are defined as low-income countries confronting severe structural impediments to sustainable development (United Nations, n.d. -d). There are around 46 nations in the world have been designated as LDCs, which are three Oceania countries, nine Asia countries, one Latin America and the Caribbean country and 33 Africa countries. Some of LDCs have been working towards an accelerated growth into developing countries successfully, while some are gradually making their way there, with others still struggling to survive. The list of nations in tabulated in Table 2.6 and the list of LDCs will be reviewed triennially by the Committee for Development Policy (CDP).

Table 2.6

List of the Least Developed Countries (LDCs)

1. Afghanistan	2. Angola	3. Bangladesh	4. Benin
5. Bhutan	6. Burkina Faso	7. Burundi	8. Cambodia
9. Central African Republic	10. Chad	11. Comoros	12. Congo, Dem. Rep.
13. Djibouti	14. Eritrea	15. Ethiopia	16. Gambia
17. Guinea	18. Guinea-Bissau	19. Haiti	20. Kiribati
21. Lao PDR	22. Lesotho	23. Liberia	24. Madagascar
25. Malawi	26. Mali	27. Mauritania	28. Mozambique
29. Myanmar	30. Nepal	31. Niger	32. Rwanda
33. Sáo Tomé and Príncipe	34. Senegal	35. Sierra Leone	36. Solomon Island

Table 2.6 Continued

37. Somalia	38. South Sudan	39. Sudan	40. Timor-Leste
41. Togo	42. Tuvalu	43. Uganda	44. Tanzania
45. Yemen	46. Zambia		

Source: (UNCTAD, n.d. -b)

Three main criteria have been used to identify those countries, which are human asset index (HAI), gross national income (GNI) per capita, and economic vulnerability index (EVI), whereby the EVI and HAI are indices. They include 8 (eight) and 5 (five) indicators respectively. These indicators are used to characterize the condition of the countries, like inadequate institutional and productive capacity, extreme poverty, and other vulnerabilities and constraints. Table 2.7 contains the 13 (thirteen) indicators of HAI and EVI.

Table 2.7

Indicators of human asset index (HAI) and economic vulnerability index (EVI)

Human Asset Index (HAI)		**Economic Vulnerability Index (EVI)**	
No.	**Indicator**	**No.**	**Indicator**
1.	Percentage of undernourished population	1.	Population
2.	Mortality rate under-five	2.	Remoteness
3.	Maternal mortality rate	3.	Merchandise export concentration
4.	Gross secondary school enrolment ratio	4.	Share of forestry, agriculture, fishing, and hunting

Table 2.7 Continued

Human Asset Index (HAI)		Economic Vulnerability Index (EVI)	
No.	**Indicator**	**No.**	**Indicator**
5.	Adult literacy rate	5.	Share of population in low elevated coastal zones
		6.	Instability of exports of goods and services
		7.	Victims of natural disasters
		8.	Instability of agriculture production

Source: The Department of Economic and Social Affairs of the United Nation Secretariat (UN/DESA) (United Nations, n.d. -a & United Nations, n.d. -b)

The UN/DESA is responsible for overseeing the list of LDCs. Technically, once a country has been identified as an LDC, the CDP formally notifies the Economic and Social Council of the United Nations (ECOSOC) for endorsement. Then, the country will be formally notified by the Secretary-General of UN and the inclusion takes effect immediately. Under the definition of UN/DESA, a country is a LDC if its per capita GNI is at most $1,025, HAI is at most 60 and EVI is at least 36 (UN-OHRLLS, n.d.).

The weakest segment of the international community is under LDCs. Their social and economic development is not only a major challenge for themselves, but also for the international community. Hence, the UN arranges several initiatives to remove the obstacles and challenges of these countries in order to reduce poverty, help them to achieve globally agreed development goals, and thus enable them to graduate from LDC category. For a country to graduate from the LDCs, the country should score its per capital GNI between $1,230 and $2,460 income-only, HAI at least 66 and EVI at most 32. The country is eligible to graduate if it has met the score required at two consecutives triennial reviews (UN-OHRLLS, n.d.). An example of assessment of LDC indicators on four countries is summarized in Table 2.8.

Table 2.8

An example of LDC indicator assessment on four South Asian countries. (United Nations, n.d. -c)

Country	**Inclusion Year**	**GNI per capita**	**HAI**	**EVI**
Bangladesh	1975	$1,827	75.3	27.2
Bhutan	1971	$2,982	79.5	35.7
Myanmar	1987	$1,263	73.9	24.3
Nepal	1971	$1,027	74.9	24.7
Graduation		*$1230 or above*	*66.0 or above*	*32.0 or below*
LDCs Average		*$1229*	*53.1*	*41.3*

GNI = Gross National Income

HAI = Human Assets Index

EVI = Economic Vulnerability Index

Source: United Nations, n.d. –c

2.4.1 Digitization of Higher Education Institutions in the Least Developed Countries

In a statistical analysis conducted in 104 countries by the International Telecommunications Union (2020), only 38.3% of the youth population in Least Developed Countries (LDCs) are online. Amongst the young individuals not using the Internet, nine out of 10 live in Africa or Asia and the Pacific. Barely 7.2% of households in LDCs have access to computers and 16.3% have access to the Internet, heavily relying on connections at work, schools/universities, or other shared public networks, like internet cafés (International Telecommunication Union, 2020). Although 75% of the population in LDCs have a mobile cellular subscription, only 33% have active mobile-broadband subscriptions. Although considerable progress has been made in recent years, affordability remains a challenge for LDCs (International Telecommunication Union, 2020). With limited access to online platforms, many Higher Education Institutions (HEIs) in LDCs are unlikely to have access to the necessary digital tools and resources, providing a sub-standard education, as a result, is quite possible to be delivered to their nation.

Digital transformation cannot materialize in a vacuum – it demands substantial investment capital, foundation of nationwide digital systems, and over all vital physical infrastructure (electricity and internet access). It is the combined efforts of these digital essentials that foster widespread adoption and innovation. But, where almost 1 billion people in the world currently are out of electricity, and less than a quarter of the population in lower-income countries are out of internet reach, this is a daunting challenge (International Telecommunication Union, 2020). In remote and rural locations, which is the generic scenario in the LDCs, infrastructure costs are too high for traditional networks to be a feasible option, primarily due to the lack of the connection to the main network, which is quad times more expensive than in urban areas. As per the International Telecommunication Union (ITU), most people, even those in the poorest countries, are under cellphone signal coverage already.

One of the main challenges is to make sure that everyone can gain access to and pay for the services once the internet infrastructure is eventually developed. (eTrade for all, 2019). The lack of an independent regulating telecommunications framework, the inequitable business field for vendors, inadequate public sector participation, expensive internet connectivity, inadequate energy supplies and logistical support, ill-developed financial technology industry, along with weak regulatory and legal frameworks are all contributing factors to the lag in digitalization (International Telecommunication Union, 2020), not just in academia, but in the overall economy. A country's infrastructure, physical and digital, is mainly developed by its government legislation and policies, affecting the actual and perceived benefits and costs, as well as addressing existing challenges or create obstacles for disadvantaged groups (minorities, women, disabled, etc.). Beyond changes to legislation, development also requires a considerable investment in both soft and hard infrastructure, including a focus on trade facilitation, energy, ICT, and transport (UNCTAD, n.d. -a).

Besides, social norms, on a macro level, contribute to behavioral change in attributes from education systems to work practices to governance regulations (Yamin et al., 2019). This effect becomes an even more potent influence of an individual's chosen behavior when factoring in approval and disapproval from others. The more extreme the perceived condemnation and resulting sanctions are, the more likely that an individual preference for a changed behavior would be overridden (Tankard & Paluck, 2016). Social influence is one of the crucial keys to social change. In order to get a society in its entirety to widely accept and adopt a new practice, such as digitalization, it requires consistency, commitment, and flexibility from the minority to the majority members of the society. Gradually as the idea ripples through society, resulting in a snowball effect that eventually brings about societal change (Mcleod, 2017). But this phenomenon seems to have little to no effect within the communities of LDCs in terms of digitalization. It is a delayed process, given the pre-existing constraints of low digital literacy and poor digital infrastructure (International Telecommunication Union, 2020). This limits the level of social influence on rolling out a mass digitalization effort, whether that is in the academic supply chain or otherwise (Digital Economy Report, 2019). A summary of causes that drawback the digitalization process in the LDC and their effects are tabulated in Tables 2.9 and 2.10.

Table 2.9

Cause of digitization drawback in the LDCs

Cause	**Author (year)**
Affordability and Poverty	International Telecommunication Union (2020), The World Bank, (n.d.)
Digital literacy	UNESCO (2018), Zelezny-Green et al. (2018)
Access to devices and internet connectivity	International Telecommunications Union (2020), Zelezny-Green et al. (2018)

Table 2.9 continued

Cause	Author (year)
Physical infrastructure - Inadequate energy supplies, insufficient logistical support	International Telecommunications Union (2020)
Infrastructure costs are too high in rural areas	International Telecommunications Union (2020)
Absence of Independent regulating telecommunications framework along with along with weak legal and regulatory frameworks	International Telecommunications Union (2020)
Inequitable playing field for operator and insufficient public sector participation	International Telecommunications Union (2020)
High costs for internet connectivity	International Telecommunications Union (2020)
Lack of Social influence	Tiwari and Srivastava (2020), Digital Economy Report (2019), Mcleod (2017)

Table 2.10

Effect of digitization drawback in the LDCs

Effect	Author (year)
Nearly 30% of the illiterate population is concentrated in the LDCs, where 20% are young people. South-East Asia and Sub-Saharan Africa account for the majority of the illiterate population in the world.	The Sustainable Development Goals Report (2019), the World Youth Report (2018)

Table 2.10 continued

Effect	Author (year)
Only 38.3% of the youth population in Least Developed Countries (LDCs) are online	International Telecommunications Union (2020)
Barely 7.2% of households in LDCs have access to computers and 16.3% have access to the Internet	International Telecommunications Union (2020)
Only 33% have active mobile-broadband subscriptions	International Telecommunications Union (2020)
Less than half of the population in 40 out of 84 countries in the world possesses basic computer skills.	International Telecommunications Union (2020)

Bangladesh is chosen as the scope of this study representing the LDC countries. Developed and developing countries have been adopting digitization in higher education institutes as mentioned in the previous sections of the chapter. Unfortunately, LDCs are in a disadvantageous condition when it comes to digitization which is also reflected in most of the reports of the UN and ITU. The finding of lack of Digital Supply Chain studies in higher education institutes along with the LDCs unpreparedness for digitization combined are the motivations of this research.

With technology comes advancement that requires acceptance in order to bring about adoption. And the pace of the process itself is a variant, contingent upon different contributing factors. In HEIs, digitalizing operations and adapting e-learning is a major change that is hindered by the level of knowledge, skills, and of course, attitude of stakeholders, from students to staff, to even guardians, management, and corporations, towards embracing new technologies.

The World Bank published a Digital Adoption Index (DAI) in 2016, where the standing of the countries was reported as tabulated in Table 2.11. It is a worldwide index which is measured across three dimensions of the country's economy: people, government, and business (The World Bank, n.d.).

Table 2.11

Digital Adoption Index (DAI) of South Asian Countries

Country	**DAI Score**
Bangladesh	0.371819019
Bhutan	0.443957299
India	0.510771692
Maldives	0.507852614
Myanmar	0.259412646
Nepal	0.365238547

Source: The World Bank, n.d.

Unfortunately, the index was not updated after 2016. There is another one called ICT Development Index (IDI) which was developed by the International Telecommunication Union (ITU). The worldwide report was last posted in 2017 as tabulated in Table 2.12.

Table 2.12

ICT Development Index (IDI) of South Asian Countries

IDI 2017 Rank	Country	IDI 2017 Value	IDI 2016 Rank	IDI 2016 Value
147	Bangladesh	2.53	146	2.37
121	Bhutan	3.69	119	3.58
140	Nepal	2.88	139	2.60
135	Myanmar	3.00	140	2.59
134	India	3.03	138	2.65
85	Maldives	5.25	86	4.97

Source: International Telecommunication Union, n.d.

The ICT Development Index (IDI) is a composite index which was reported annually combining 11 indicators. But unfortunately, due to complexities brought by newly introduced indicators, the index was postponed after 2017. However, ITU still reports some relevant data annually as shown in Table 2.13.

Table 2.13

Digital Infrastructure in LDCs of South Asia

Country	Category	Year		
		2018	2019	2020
Bangladesh	Subscribers of Active mobile-broadband per 100 inhabitants	41.275	52.786	53.018
	Subscribers of fixed broadband per 100 inhabitants	4.990	4.959	5.782
	Population coverage by a mobile-cellular network (%)	99.6	99.6	99.61

Table 2.13 continued

Country	Category	Year		
		2018	2019	2020
Bhutan	Subscribers of Active mobile-broadband per 100 inhabitants	101.641	99.900	89.286
	Subscribers of fixed broadband per 100 inhabitants	1.432	1.150	0.407
	Population coverage by a mobile-cellular network (%)	98	98	98
Myanmar	Subscribers of Active mobile-broadband per 100 inhabitants	89.912	92.689	NA
	Subscribers of fixed broadband per 100 inhabitants	NA	NA	NA
	Population coverage by a mobile-cellular network (%)	95.15	NA	NA
Nepal	Subscribers of Active mobile-broadband per 100 inhabitants	55.547	47.518	NA
	Subscribers of fixed broadband per 100 inhabitants	1.821	2.819	NA
	Population coverage by a mobile-cellular network (%)	92.47	NA	NA
Maldives	Subscribers of Active mobile-broadband per 100 inhabitants	55.707	50.634	46.621
	Subscribers of fixed broadband per 100 inhabitants	1.343	1.402	1.615
	Population coverage by a mobile-cellular network (%)	100	100	100

Table 2.13 continued

Country	Category	Year		
		2018	2019	2020
India	Subscribers of Active mobile-broadband per 100 inhabitants	37.496	47.043	52.545
	Subscribers of fixed broadband per 100 inhabitants	1.343	1.402	1.615
	Population coverage by a mobile-cellular network (%)	97.000	99.060	99.060

Source: International Telecommunication Union, 2020

Another similar observation is also evident in the Digital Readiness Score developed by Cisco System Incorporation. Based on their last report published in 2019, the standing of the countries is tabulated in Table 2.14. A country's digital readiness score is based on seven components- Basic Needs, Human Capital, Business and Government Investment, Start-Up Environment, Ease of Doing Business, Technology Infrastructure, Technology Adoption, which are standardized and summed to determine an overall digital readiness score (Cisco System, Inc. n.d.).

Table 2.14

Digital Readiness Score 2019

Country digital	**Readiness Scores**
Bangladesh	8.53
Bhutan	NA
India	9.46
Maldives	NA
Myanmar	8.08
Nepal	9.27

Source: Cisco System, Inc. n.d.

According to a recent census report, the Bangladesh's current population is 165,158,616 (165 million 58 thousand 616). Out of which, 10 (ten) percent of the total population belongs to 15-19 age group, 9 (nine) percent are in 20-24 group and 8.71 percent are in 25-29 group. It is evident that a major chunk of the population is youth. On average, every year 2 million people join the workforce (Rahman, 2022). There are 157 universities in Bangladesh where 12,30,198 students are enrolled (University Grants Commission of Bangladesh, 2020). Affordability, Poverty, Digital literacy, Physical infrastructure, insufficient logistical support, Infrastructure costs, and many other phenomena were identified as the drawbacks of digitization in countries like Bangladesh and eventually they also impact on higher education institutions (International Telecommunication Union, 2020, The World Bank, n.d., UNESCO, 2018, Zelezny-Green et al., 2018). Data presented in previous sections, like, Digital

Adoption Index (DAI), ICT Development Index (IDI) and Digital Readiness Score 2019 are also reflection on this issue. Hence, the scope of this study is narrowed down on the higher education institutes of Bangladesh.

2.5 Digital Literacy in LDC

It is not a surprise when 775 million people in the world, including 103 million young people, still struggle to read or write according to UNESCO. Nearly 30% of the illiterate population is concentrated in the LDCs, where 20% are young people (World Youth Report, 2018). A three-fifth of the group is made up of women, with Sub-Saharan Africa, and South-East Asian accounting for the majority of the illiterate population in the world (The Sustainable Development Goals Report, 2019). Those suffering from low literacy as well as digital literacy (UNESCO, 2018) are on a double-edged knife. Even beyond fundamental skills of literacy and numeracy, people need to have a bare minimum level of digital literacy in order to be fully functional in a society driven by knowledge today, in terms of active citizenship, social inclusion, work opportunities, as well as personal fulfillment and development (Zelezny-Green et al., 2018). Less than half of the population in 40 out of 84 countries in the world possesses basic computer skills such as copying a file or sending an attachment through e-mail. The number is considerably lower for more complex activities such as using the spreadsheet or downloading and installing new software. In 60 of the countries, it is less than 50% (International Telecommunication Union, 2020).

Sayed and Mamun-ur-Rashid (2021), in their study, found that of citizens of Bangladesh struggles to avail ICT aided services due to their low digital literacy. Similar observation was also found in other separate studies where digital literacy was identified as a crucial contributor to ICT enabled services. Adequate digital literacy aids widespread anytime access to e-health service (Alam, 2018). Aziz (2020) in his exploratory research conducted on the National ICT Policy of Bangladesh published in 2015 identified that even though policy focuses mainly on infrastructural development across the country by making rapid ICT network expansion and services, but it lacks sufficient detail on its realization. There is hardly any action plan towards its goal of affordable accessibility of ICT infrastructure, particularly in rural areas of Bangladesh. It is important to provide specific guidelines on how communities will overcome socio economic challenges to access ICT resources and contribute to the increase of digital literacy. Even though Bangladesh government has established task force for digitizing the education at national level, but accessible guidelines and clear mechanisms are important factors to ensure its real impact. In Bangladesh, there is an awareness of digitization need for augmenting education quality, equity, and efficiency at the national level. However, low digital literacy has been a constraint in realizing this awareness intro reality (Lim et al. 2020). It has been also evident in research that in countries like Bangladesh, digital literacy can contribute significantly to bridge the digital divide (Islam & Inan, 2021).

Digital literacy is undoubtedly an important factor in assessing the digital service impact on the stakeholders of higher education institutes in a country like Bangladesh, and hence, it will be adopted as a component of the research framework in this study.

2.6 Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2)

Numerous research has been conducted to identify factors that predict user's acceptance of technology, like Technology Acceptance Model (TAM) of Davis, 1989, Diffusion of Innovation by Everett Rogers, 1995 and the Unified Theory of Acceptance and Use of Technology (UTAUT) unified by Venkatesh, 2003. One of the most comprehensive technology acceptance theories is UTAUT. The UTAUT, a model originally established by Viswanath Venkatesh, Michael G. Morris, Gordon B. Davis and Fred D. Davis (Venkatesh et al., 2003), correlated user intentions and acceptance of information technology and the subsequent usage behavior. The initial idea was built on four key constructs, which are performance expectancy, effort expectancy, social influence, and facilitating conditions. All of these four constructs are dependent on the variables of gender, age, experience, and voluntariness of users, determine the usage intention and behavior patterns. UTAUT is combined of eight other theories including Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Motivational Model (MM), the Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), a combination of theory of Planned Behavior/Technology Acceptance Model (C-TPB-TAM), and Social Cognitive Theory (SCT) (Jakkaew & Hemrungrote, 2017). For a better undestanding, the eight theories is presented in Figure 2.6.

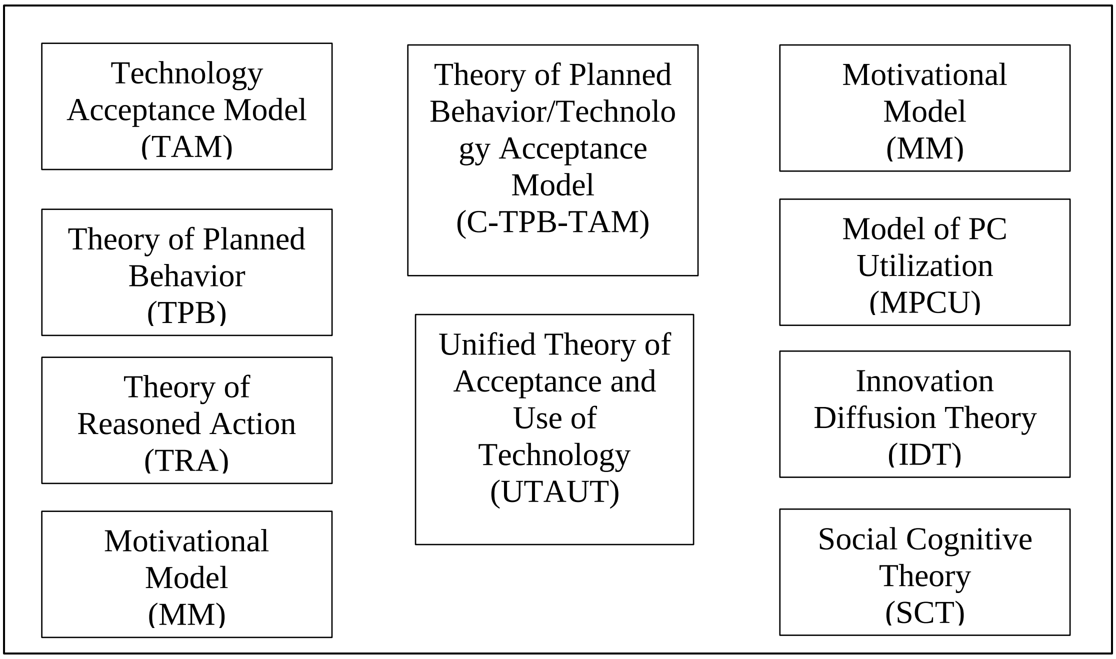

Figure 2.6. The Eight Theories in UTAUT Model

Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the combination of theory of Planned Behavior/Technology Acceptance Model (C-TPB-TAM) are briefly discussed in the following sections.

2.6.1 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is a well-known theory that has been used in various fields, including education, to understand the factors that influence individuals' intention to use and accept technology (Davis, 1989). In the context of HEIs, the TAM has been used to study students' and teachers' acceptance of various technologies, such as learning management systems, mobile learning, and educational software.

In a study by Mutambik et al. (2019), TAM was used to investigate Saudi Arabian university students' acceptance of e-learning. The study found that both perceived usefulness and ease of use had a significant effect on students' intention to use e-learning. Similarly, in a study by Almaiah, M. A. (2018) on Jordanian university students' acceptance of mobile learning, TAM was used to explain the factors that influence students' intention to use mobile learning. The study found that perceived ease of use, perceived usefulness, and attitude towards mobile learning were significant predictors of students' intention to use mobile learning.

In another study by Grandón et al. (2021) on Iranian students' acceptance of educational software, TAM was used to investigate the factors that affect students' intention to use the software. The study found that perceived usefulness and perceived ease of use had significant effects on students' intention to use educational software.

In a study by AL-Nuaimi et al. (2022) on Omani university students' acceptance of learning management systems, TAM was used to identify the factors that influence students' intention to use the systems. The study found that perceived usefulness, perceived ease of use, and perceived enjoyment were significant predictors of students' intention to use learning management systems.

Overall, these studies suggest that TAM can be a useful framework to understand students' and teachers' acceptance and intention to use various technologies in the context of HEIs. The perceived usefulness and perceived ease of use are the two significant factors in the TAM that affect users' intention to use technology in the educational context.

2.6.2 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) was first proposed by Fishbein and Ajzen in 1975, and it has been widely applied in various fields, including the field of education (Ajzen & Fishbein, 1980). The TRA suggests that an individual's behavioral intention is the main predictor of their behavior, and this intention is influenced by their attitude towards the behavior and subjective norms (Ajzen & Fishbein, 1980).

In the context of HEI, the TRA has been applied to study various behaviors such as student attendance in university events by Harb et al. (2021). One recent study applied TRA to investigate the intention of faculty members to adopt cloud computing in HEI (Asiaei & Ab. Rahim, 2019). The study found that attitude, subjective norm, and perceived behavioral control had significant effects on faculty members' intention to adopt cloud computing in HEI.

Another recent study applied the TRA to explore the factors that influence the intention of students to use mobile learning in HEI (Al-Rahmi et al., 2021). The study found that attitude, subjective norm, and perceived behavioral control had a positive and significant effect on students' intention to use mobile learning in HEI.

Overall, the TRA has proven to be a useful framework for understanding and predicting behavior in the context of HEI. Its focus on behavioral intention, attitudes, and subjective norms can provide insights into the factors that influence the adoption of various technologies and practices in HEI.

2.6.3 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) is a social psychological theory that has been used to understand and predict human behavior in various fields, including in the adoption of new technologies in higher education institutions (HEIs). According to TPB, intention to perform a behavior is determined by three factors: attitude toward the behavior, subjective norm, and perceived behavioral control (Ajzen, 1991). In the context of technology adoption, TPB has been used in combination with other relevant models to understand the factors that influence the intention to adopt and use new technologies.

Several studies have examined the application of TPB in the context of technology adoption. For instance, a study by Lung-Guang, N. (2019) applied TPB combined with self-regulated learning (SRL) to investigate the decision-making determinants of students participating in massive open online courses (MOOCs). The study found that prediction power of the integrated model was superior to that of the theory of planned behavior or the self-regulated learning model in the online learning context.

Gómez-Ramirez et al. (2019), in their study to explore the acceptance of Colombian university students to accept m-learning using TPB and TAM, found that perceived usefulness and attitude have a significant influence on students' acceptance of m-learning

Another study by AlBar and Hoque (2019) applied TPB combining with TAM to investigate the factors that influence the intention to e-health services in Saudi Arabia.

The study found that attitude and subjective norm significantly influence patient behavioral intention.

In a study by Mohammed and Ferraris (2021), TPB was used to investigate the factors that influence the participation in social media in Saudi Arabia. The study found that attitude toward e-learning, subjective norm, and perceived behavioral control significantly influenced the intention to use e-learning.

Overall, the application of TPB in the context of technology adoption in HEIs has provided insights into the factors that influence the intention to adopt and use new technologies. These insights can inform the development of strategies to promote the adoption and use of new technologies in HEIs.

2.6.4 Combination of the TPB and TAM (C-TPB-TAM)

The combination of the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM), known as C-TPB-TAM, has been widely used in research related to technology adoption in higher education institutes (HEIs). This model integrates the TPB's focus on attitudes, subjective norms, and perceived behavioral control with TAM's emphasis on perceived usefulness and perceived ease of use.

A study by Afacan Adanır and Muhametjanova (2021) found that the C-TPB-TAM model could predict Turkey and Kyrgyzstan university students' intention to use mobile learning technology. Another study by Szymkowiak and Jeganathan (2022) investigated Indian university students' acceptance of e-learning using the C-TPB-TAM model and found that perceived usefulness was the most significant predictor of intention to use e-learning. Similarly, Kim et al. (2021) used the C-TPB-TAM model to investigate Korean students' acceptance of online learning and found that perceived usefulness and perceived ease of use significantly predicted their intention to use mobile learning.

Furthermore, a study by Nguyen et al. (2022) used the C-TPB-TAM model to investigate the factors that influence the intention of using building information modeling in Vietnam. The study found that perceived usefulness, perceived ease of use, and subjective norm were significant predictors of intention to use the e-learning platform. Another study by Le et al. (2022) used the C-TPB-TAM model to investigate Vietnamese university students' acceptance of E-Learning and found that perceived usefulness and perceived ease of use significantly influenced their intention.

Overall, the C-TPB-TAM model has been found to be a useful framework for understanding technology adoption in HEIs. The integration of the two models allows for a more comprehensive examination of the factors that influence intention to use technology in educational settings.

2.6.5 Consolidated in UTAUT2

Consolidated through a mix of previously established relevant theories of information technology and user behavior, UTAUT quickly gained validation in multiple fields for its cohesive application across the spectrum. While UTAUT by Venkatesh et al. is widely accepted, three additional buildings have been incorporated into UTAUT: hedonic encouragement, quality worth and habit. Compared to UTAUT, UTAUT2's proposed modifications have significantly improved the variation described in behavioral intent (56%–74%) and in technology usage (40%–52%). Such findings address theoretical and management implications. As the extension of the theory, the UTAUT2 encompasses heterogeneous factors that affect user acceptance of technology, as more and more HEIs make the shifts from manual to automated and online, or in some cases, hybrid. UTAUT is a significant improvement compared to other models or theories of used for adoption of technology. In terms of explanatory power, it surpasses others by 20%, indicating higher accuracy in predicting the key constructs of technology acceptance and use (Jaradat et al., 2020). The additional four key moderating constructs have further increased their predictive power. The UTAUT is one of the main theoretical models for used in studies for assessing the technology adoption in developing countries and is already regarded as the model that shows a higher degree of validity and consistency (Jaradat et al., 2020).

According to Venkatesh et al. (2003), there are four (4) key constructs that influence a user's purpose and use of information technology. First, the expected results, it is the degree to which a person believes he or she can use the system to achieve job performance gains. Secondly, the presumption of commitment. It is the degree of ease with which the device is used. Thirdly, the conditions which is the degree to which a person assumes that the program can be maintained in organizational and technological infrastructure. Fourth, the power of culture. It is to the degree to which a person sees that others believe that the new method should be used.

A summary of research is listed in Table 2.15 where UTAUT2 model has been used to study the technology acceptance along with the technique used. The table also contains a segment where the studies are conducted in the educational institutes.

Table 2.15

Summary of Research Used UTAUT2

Domain	Technique Used	Author (Year)
Educational Institutes		
Adoption of Cloud Computing in Higher Educational domain	Structural Equation Modeling (SEM) using WarpPLS 5.0	Jaradat et al. (2020)
Utilization of LMS-enabled blended learning in distance higher education	Structural Equation Modeling (SEM) using Smart PLS 3.6.2	Bervell and Arkorful (2020)
Explain the University Students' Acceptance of Mobile Learning System	Structural Equation Modeling (SEM)	Almaiah et al. (2019)
Adoption of Cloud Computing in Higher Educational domain	Structural Equation Modeling (SEM) using WarpPLS 5.0	Jaradat et al. (2020)
Utilization of LMS-enabled blended learning in distance higher education	Structural Equation Modeling (SEM) using Smart PLS 3.6.2	Bervell and Arkorful (2020)
Explain the University Students' Acceptance of Mobile Learning System	Structural Equation Modeling (SEM)	Almaiah et al. (2019)
Factors affecting students' perception of E-Learning system in universities	Multiple Linear Regression (MLR), Structural Equation Modeling (SEM) using Smart PLS	Ahmad et al. (2020), Salloum and Shaalan (2018)
Factors influencing the behavioral intention of users towards mobile learning	Structural Equation Modeling (SEM) using Smart PLS	Chao (2019)

Table 2.15 continued

Domain	Technique Used	Author (Year)
Factors in adopting an Electronic Records Management System (ERMS) in the Educational Sector	Structural Equation Modeling (SEM) using Smart PLS	Mukred et al. (2019)
Clustering university teaching staff through UTAUT: Implications for the acceptance of a new learning management system	Cluster Analysis	Garone et al. (2019)
Understand the use of virtual classroom principle in higher education	ANOVA Analysis	Aditya and Permadi (2018)
Adoption and Usage of Mobile Learning in universities	Structural Equation Modeling (SEM)	Mosunmola et al. (2018)
Explain behavioral intention towards usage of M-learning	Structural Equation Modeling (SEM)	Thongsri et al. (2018)
Understanding Student Perceptions Using Google Classroom	Person's correlation	Jakkaew and Hemrungrote (2017)
Predicting adult learners' online participation	Hierarchical Multiple Regression Analyses	Diep et al. (2016)
The influence of learning value on learning management system use	Structural Equation Modeling (SEM)	Ain et al. (2016)
Other domains		
User's perception and acceptance of robots and driverless vehicles with aspect of personal economy	Hierarchic Multiple Regression Analysis (Path Analysis) using SPSS	Kencebay (2019)

Table 2.15 continued

Domain	Technique Used	Author (Year)
Factors Influencing Online Hotel Booking	Structural Equation Modeling (SEM) using WarpPLS 4.0	Chang et al. (2019)
Customer acceptance of mobile Marketing	Structural Equation Modeling (SEM) using PLS	Eneizan et al. (2019)
Acceptance and usage of mobile banking	Structural Equation Modeling (SEM) using PLS	Kwateng et al. (2019)
Factors influencing the behavioral intention of users to use mobile learning	Structural Equation Modeling (SEM) using PLS	Chao (2019)
Factors influencing internet banking among Jordanian customers	Structural Equation Modeling (SEM) using AMOS	Alalwan et al. (2018)
Factors Influencing Continuous Intention to use and adapt E-Payment	Structural Equation Modeling (SEM) using PLS 2.0 M3	Putri (2018)
Factors affecting users' perception and intention to Use E-government Services	Structural Equation Modeling (SEM)	Rallis et al., (2018)
The Role of 'Price Value' for understanding consumer's technology adoption	Meta-analysis	Tamilmani et al. (2018)
Perception of customers towards fashion brands retail websites regarding e-word-of-mouth and performance expectancy	Structural Equation Modeling (SEM) using Smart PLS 2.0	Loureiro et al. (2018)
Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT)	Meta-Analytic Structural Equation Modeling (MASEM)	Dwivedi et al. (2017)

Table 2.15 continued

Domain	Technique Used	Author (Year)
Citizens' adoption of an electronic government system	Structural Equation Modeling (SEM) using AMOS	Rana et al. (2017)
Predicting adult learners' online participation	Hierarchical Regression Analyses	Diep et al. (2016)
The influence of learning value on learning management system use	Structural Equation Modeling (SEM) using AMOS 20.0	Ain et al. (2016)
Consumer Acceptance and Use of Information Technology	Structural Equation Modeling (SEM) using PLS	Venkatesh et al. (2012)
Factors that affect members' trust belief, and behavioral intentions in virtual communities	Structural Equation Modeling (SEM) using LISREL	Wu and Tsang (2008)

UTAUT2 is a one of the widely used models for Technology acceptance studies by the researchers (Jaradat et al., 2020). It is also evident that researchers prefer to use them in the educational domain as well. Hence, in this study, the UTAUT2 model is chosen to be the main underpinning theoretical model.

For a better understanding, the framework of UTAUT2 is illustrated in Figure 2.7. Basically, the moderation effects of experience, gender, age, and voluntariness to use technology define the strength of predictors on usage intention. All of the four predictors are affected by age. Whereas, the relationships of performance expectancy, effort expectancy, and social influence are affected by Gender. On the other hand, experience moderates the relationships between facilitating conditions, social influence and effort expectancy. Finally, voluntariness of use only has a moderating effect on the relationship between social influence towards behavioral intention (Venkatesh et al., 2003).

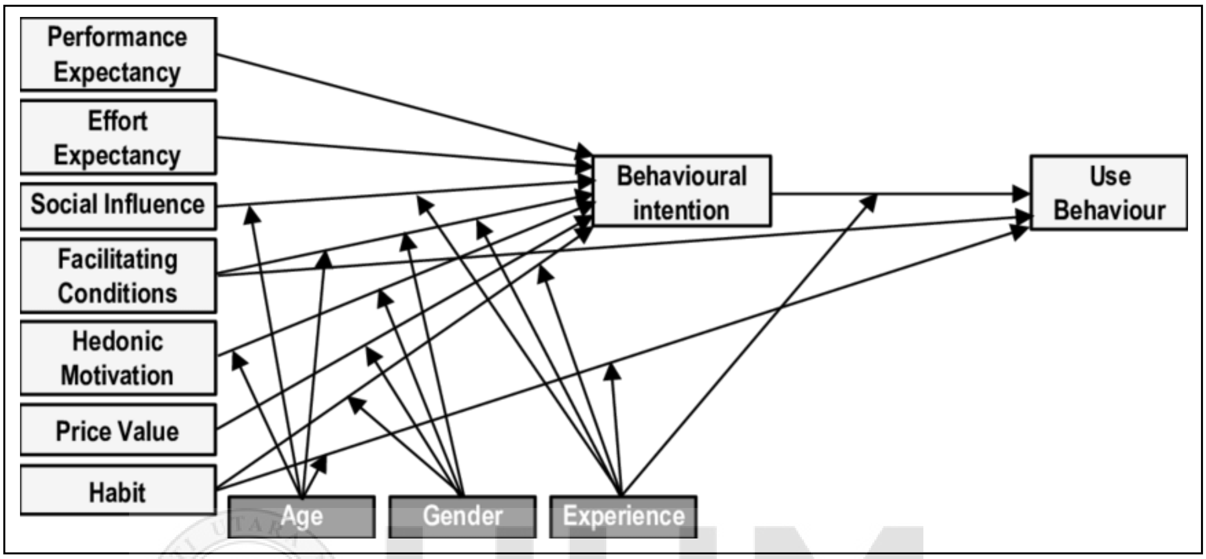

Figure 2.7. Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) (*Source:* Venkatesh et al., 2012)

Performance Expectancy, defined as "the degree to which an individual considers that using a technological system will help improve job performance" (Venkatesh et al., 2003), can be increase convenience, efficiency, accessibility, customization, as well as save on time and effort, achieved by using and adopting technology (Alalwan et al., 2018). As one of the strongest indicators of the use intention, significant in both mandatory and voluntary settings (Venkatesh et al., 2016; Zhou & Wang, 2010).

Effort Expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Users believe that the system would be easy to use, making them more likely to accept the new technology if it is flexible and requires minimal time and effort to learn and use effectively (Kwateng et al., 2019). The effect of the construct, however, does tend to become less and less significant over an extended period of usage (Chauhan & Jaiswal, 2016; Gupta et al., 2008). People tend to perceive that the new technology would be easy to use - free of effort in way. But whether the technology is in fact, actually easy to use or not, is another contributing factor as users are more likely to become reluctant if it requires more effort, as well as whether it is comparatively difficult to use or understand. These may affect a user's acceptance of the technology negatively. Again, this also has a relative impact on the consumer's usage and behavior in mandatory and voluntary settings alike (Huang & Kao, 2015). Users expect that the system's usage will reduce their efforts (energy and time) in doing work, creating a sense of comfort when using it (Rahmi & Frinaldi, 2020).

Social Influence or "the degree to which an individual perceives that others believe s/he should use the new technology", especially when it is mandated (Venkatesh et al., 2003). The level of effect on a user's adoption of new technology tends to be influenced by the opinion of friends, family, relatives, colleagues, etc. (Bervell & Arkorful, 2020). When the use of such technology is required, for classes or work, it is a matter of compliance rather than personal preference (Venkatesh & Davis, 2000), which may be why its effect varies across studies on the application of the UTAUT or UTAUT2 model (Chauhan & Jaiswal, 2016; Zhou et al., 2010). It measures the level of importance of using the new technology perceived by the user use (Briz-Ponce et al., 2016) or the limit to which an individual is persuaded with peer pressure for using a new technology (Wairimu et al., 2019). Users want to be acknowledged by their social circles (at school, amongst friends and family, at work, etc.) for using new technology. The construct depends on the norm, where there is a perceived pressure from the society to act in a certain way, the social factor, which is the someone's own perception of the societal culture, and one's own image that they believe will be enhanced amongst their peers by adopting new technologies (Huang & Kao, 2015). The amount of confidence from others makes a positive impact on a user's adaptation and utilization of technology, like support from teachers, encouragement from organizations, impact of social trends, etc. Not only does this enable the user's trust in the technology, but also significantly improves individual and team performances (Rahmi & Frinaldi, 2020).

Facilitating Condition, "the degree to which an individual believes that an organization's technical infrastructure is in place to support the use of the new technology" (Venkatesh et al., 2003). The notion that the environment, comprising of the IT support and infrastructure, is made more 'user-friendly' so as to make work easier (Bervell & Arkorful, 2020; Vairetti et al., 2019). It has a direct affirmative impact on the initial choice to use, but over time, the impact becomes non-significant (Venkatesh et al., 2003). A user is reassured in accepting new technology if there is a system that can help in the adoption process (Huang & Kao, 2015).

Hedonic motivation is "the fun or pleasure derived from using technology, that plays an important role in influencing technology acceptance and use" (Venkatesh et al., 2012). The internal satisfaction a user gets from using a new technology is a contributing factor to their adoption process (Kwateng et al., 2019). It is one's own motivational drive to acquire the knowledge and skills to utilize technological advancements. Determined by an individual's psychological and emotional characteristics, user intention and behavior may be triggered by their personality traits and cognitive understanding. One's hedonic experiences works as an intrinsic motivation that affects their acceptance of technology in both individual and organizational contexts (Huang & Kao, 2015). The usefulness of the adopted technology is certainly a determinant in the process, but if the user experience is not pleasant, not just in terms of ease of use or functionality, but also for the 'likeability' of the technology itself, they are unlikely to adopt or use it (Chang, 1970). When someone perceives that the use of a new technology to be easy and enjoyable, it has a positive influence on the behavior intention to actually use the technology in the long run. But the intention to use the technology is diminished if they do not perceive the use of it as not exciting and enjoyable (Chaveesuk et al., 2022).

Price Value concerns the "a user's trade-off between the perceived benefits and the financial cost of using a new technology" (Venkatesh et al., 2012). It assesses the individual's evaluation of whether the adoption of new technology offers greater advantages compared to the cost of it, or in other words, if it gives value for money (Chang et al., 2019). The price value construct in the UTAUT2 theory includes the monetary cost, quality, and expense of the technology that are most likely to motivate the user's intention and behaviors towards adopting it. The user's anticipation of the quality of the technology in comparison to the cost of using it, like the internet, computer systems, software applications, etc. are critical components is determining whether users would adopt a new technology or not (Chaveesuk et al., 2022).

Habit is "the extent to which people usually tend to exhibit behaviors routinely out of 'habit'" (Venkatesh et al., 2012). It is the users' familiarity with similar platforms that establishes a pattern in their user behavior from their previous exposure and eventually the regular use of such technologies (Kwateng et al., 2019). A user's prior behavior towards the acceptance and usage of similar technologies, together with the behavior patterns, sequences, or customs that are a regular part of their lives and the experience gathered from set routines, norms, and of course, habits of using the technology, create a reciprocal mindset of users to be more likely to accept new technologies over time. Combined, these reduce the need for training, coordination, or effort in the decision making for accepting innovative technology. Habitual intentions and usage are strong predictors of how easily or quickly one tends to adopt emerging technological products and services in their education, work, or other aspects of their lives (Huang & Kao, 2015). Users' habits are believed to influence their behavior automatically if they have already used similar technologies beforehand. Individuals with the nature of adopting new technologies are more likely to grow a habitual need to continuously do so, significantly influencing their usage intention and behavior over long periods of time (Chaveesuk et al., 2022).

Behavioral intention focuses on the likelihood that users will continue using the technology, contingent on the various constructs (Alalwan et al., 2018). It explores the conscious patterns of a user's behavior with a planned intent, measured by the conative loyalty. Users tend to be more loyal towards reusing technologies of similar nature, engaging in positive word-of-mouth. This is crucial for encouraging other users to adopt emerging technologies, as they are more likely to be willing to try it out if recommended by friends, family, or peers. The construct may not be an accurate prediction of user behavior, but it gives a better insight of the possibility for acceptance of new technology. In most cases, the intention to repurchase, the positive word-of-mouth, as well as the overall quality of usage for the technology are factors that determine the users' adoption process (Huang & Kao, 2015).

2.7 Research Gap

Based on the literature review conducted, the research gap can be identified as the lack of exploration of the applicability of digital supply chain management (DSCM) in the context of Higher Education Institutes (HEIs). While some studies have explored the concept of Academic Supply Chain management, the digitization of the supply chain in HEIs is yet unexplored. This gap is particularly relevant in the context of Bangladesh, where HEIs can play a crucial role in the country's economic development and human resource development. However, the absence of studies exploring their digital preparedness and literacy from stakeholders' perspectives is hindering their growth and competitiveness on a global level.

The concept of digital supply chain management is one of core items of Industrial Revolution 4.0. But unfortunately, the coverage of its research area is still concentrated mostly in the manufacturing industry and some in service-oriented organizations. There is hardly any study conducted exploring its applicability in the Higher Education Institutes (HEIs). Study of Academic Supply Chain were conducted by some researchers; but stakeholders' acceptance of digitization of the supply chain is yet unexplored. This study concentrates on the digitization of Academic Supply Chain management from its stakeholders' point of view and identifies the factors and their correlation with Digital Supply Chain practices in Academia.

In this study, identification of the DSC Practice factors that influences the HEI stakeholders, and their relevant weightage would help HEIs to align and adopt their technological development trajectory and manage their operations in a more digital-efficient manner.

The COVID-19 pandemic has put the whole world in a standstill situation. Even though citizens of the world are trying to cope with it and learning to live with it, but the educational institutes of the Least Developed Countries, like Bangladesh are the most affected and proven to be vulnerable in the current context. A major reason behind this catastrophic condition is their digital unpreparedness. The few educational institutes that were successful to continue their operations after the initial shock is solely due to their digital infrastructure, either because of their previous visionary decision or might have adopted on an urgent basis during the crisis. But one of the critical lessons this pandemic is teaching the HEIs is that not only the organization should have the proper infrastructure, but the stakeholders must also be digitally aware and prepared.

Now, more than ever, the relevancy of this study can be realized. Many of the HEIs in the LDCs have not been able to conduct any operation over this whole pandemic period; this might lead to a new type of digital divide. In Bangladesh online tertiary education is only provided by the government owned Bangladesh Open University. Other tertiary educational institutes are not entitled to provide online education (Mannan, 2015). But after the pandemic, there was no other alternative to online education. Due to absence of previous policy and adequate study, the majority of HEIs suffered from existing framework and infrastructure to continue operating when pandemic started.

To summarize this section, a research framework is illustrated in Figure 2.8. This research framework contains the components that are discussed in the literature study, like, Unified Theory of Acceptance and Use of Technology (UTAUT), digital literacy, digital supply chain practices, supply chain in higher education institutes and least developed countries. The framework depicts the overall objective of this research to identify the factors that influence the HEI stakeholders of the least developed countries to adopt digital supply chain practices. The components of this research framework are further specified and explained in the following Research Conceptual Framework and accordingly utilized in the following chapters.

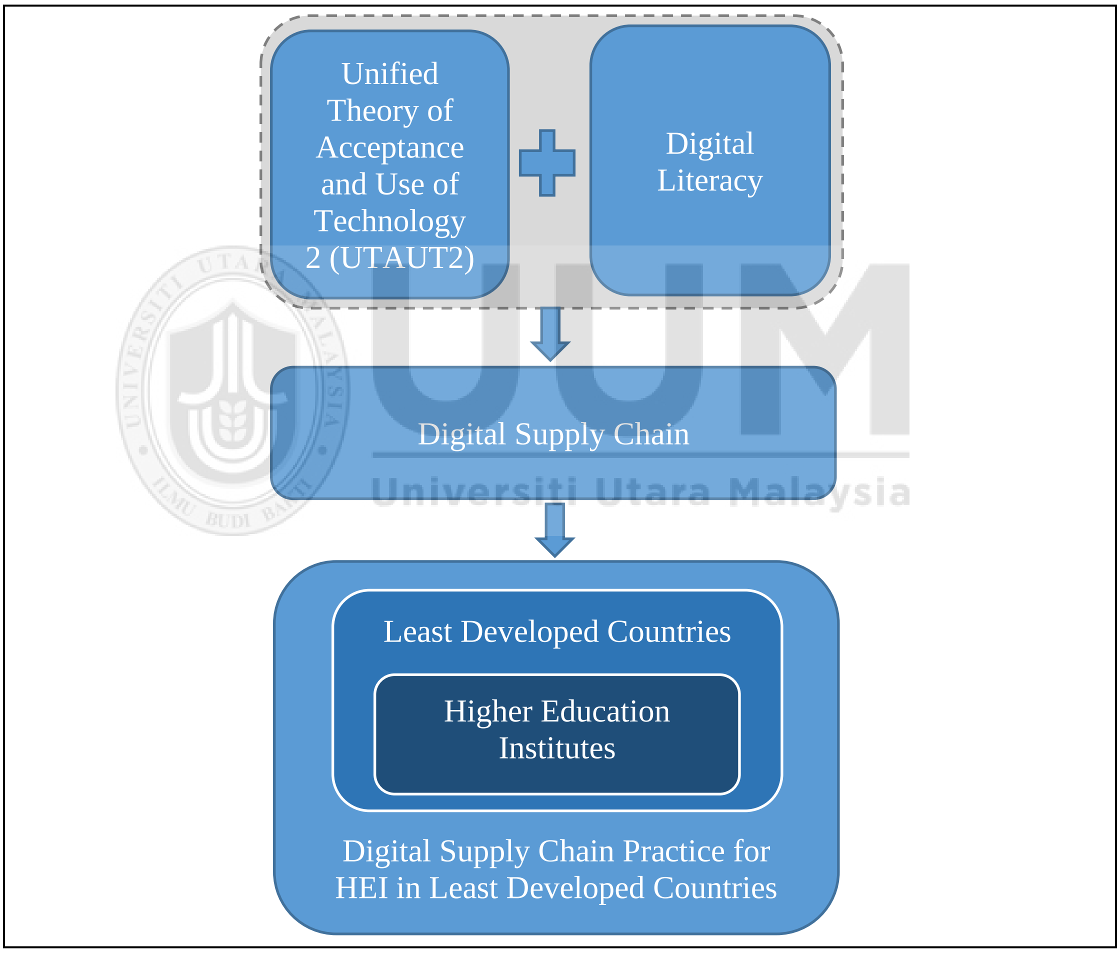

Figure 2.8. A Mapping of the Research Framework in this Study

2.8 Research Conceptual Framework

Based on the review of the literatures presented in all the previous sections and the drafted framework of research, as shown in Figure 2.8, mapped with the studied concept, the conceptual framework for this research is designed and drawn in Figure 2.9 below. This research framework is a combination of the underpinning theory – UTAUT in alignment with the extracted factors and focusing the stakeholders as mentioned in the supply chain studies conducted on HEIs. The framework also includes a new factor called Digital Literacy that was identified as a key element for the stakeholders of LDCs as evident in the relevant literature.

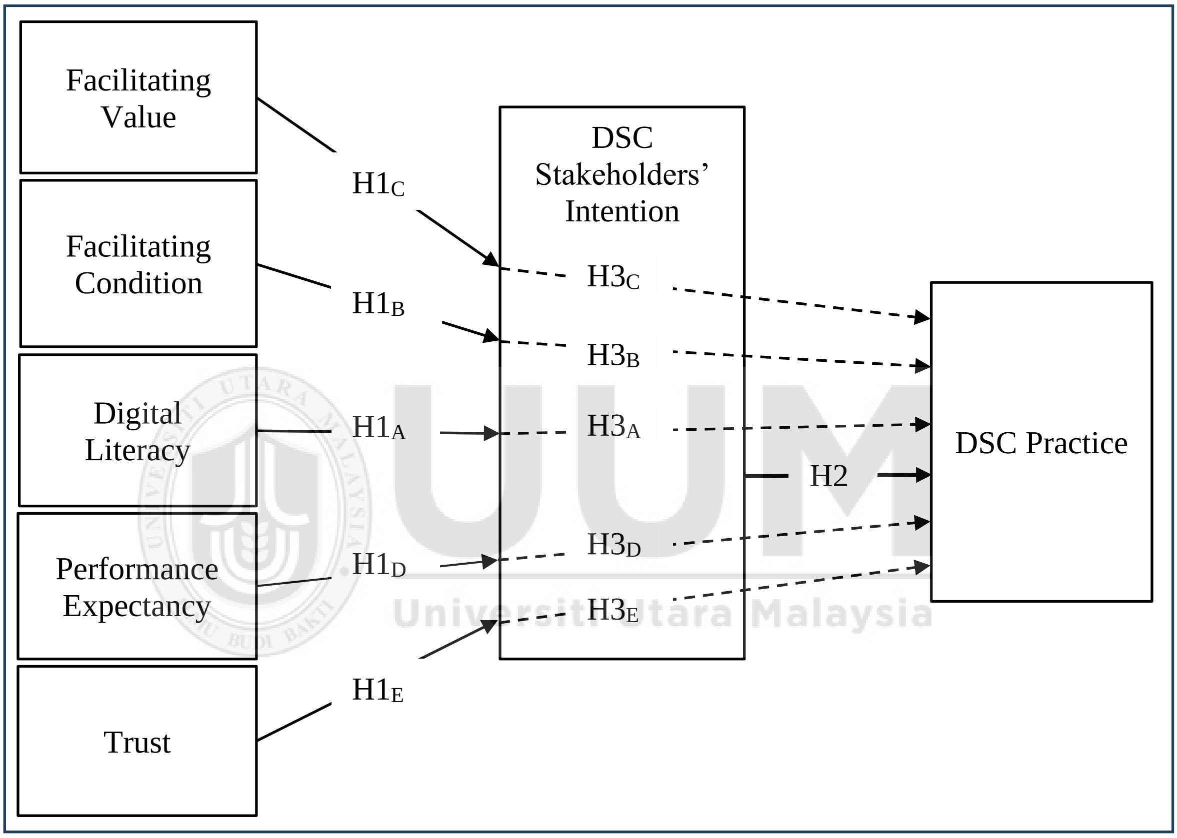

Figure 2.9. Conceptual Framework of DSC Practice model for HEIs in LDCs

Detail description of all factors – including independent variables and dependent variables are illustrated in the following sections from 2.9 – 2.15.

2.9 Facilitating Value

Facilitating value is defined from the price value of UTAUT2 model as described in the previous section. Facilitating Value refers to the perceived benefits that stakeholders perceive they will receive by adopting DSC practices. Studies suggest that perceived value is a critical factor that influences the intention and adoption of new technologies (Venkatesh et al., 2012; Wu and Zhang, 2018). The anticipated value is considered as a key pointer in comprehending and forecasting the user behavior that affects each technology’s competitive advantage over others. Price value is determined by the cost-benefit analysis of the users’ adoption of emerging technologies. If the benefits of using a technology are assessed to be greater than the costs, there is a positive impact of the price value on user’s intention. The facilitating value considers both financial and non-financial costs, which evaluates the value that the technology provides compared to the price point paid, along with the return on the time and effort invested into using the technology itself that would ultimately determine the user’s acceptance of the new technology (Huang & Kao, 2015).

In the context of HEIs, perceived value can refer to benefits such as increased efficiency, reduced costs, and improved service quality. For instance, a study by Alharbi et al. (2020) found that perceived value significantly influenced the adoption of cloud-storage among students in Malaysian HEIs. Researchers have observed that consumers’ willingness to accept and adopt new technology is significantly affected by the financial cost. The amount of price has a significant effect on buyers’ mindset (Chang et al., 2019, Eneizan et al., 2019). Chang et al., 2019 found that Facilitating Value has a significant positive effect on users' intention to adopt mobile payment services. In other words, when users perceive that a technology offers easy and convenient ways to complete tasks and achieve their goals, they are more likely to intend to adopt it. Similarly, Eneizan et al., 2019 found that Facilitating Value has a significant positive effect on users' intention to adopt mobile banking services. They also found that this effect is moderated by age and gender, indicating that the importance of Facilitating Value may vary for different demographic groups. The anticipated value is usually determined by consumers' cognitive comparison of payment that they should bear against the quality and convenience they receive. It is a positive predicator of consumer behavioral intention of adopting and using a technology (Kwateng et al., 2019, Alalwan et al., 2018, Tamilmani et al. 2018).

It is stated in the reports of the International Telecommunication Union (2020) and the World Bank (n.d.). that for LDCs, where poverty and affordability are proven challenges and part of living for many, the facilitating value is a major contributor of making their decision regarding most of their livelihoods. Hence, the adoption of digital supply chain practices of the stakeholders of HEIs in the LDCs is certainly influenced by the value that they need to bear.

In the swiftly evolving landscape of digital transformation, the concept of "Facilitating Value" has arisen as a decisive factor impacting the inclination of users to adopt and employ digital tools, particularly within the domains of developing or less developed nations. This intricate factor encompasses an array of attributes, including reasonable cost, value proposition, and the heightened potential of digital tools at a reduced expenditure, all of which significantly mold users' perceptions and choices (Human, G. et al., 2020).

In the context of developing or under-developed nations, where limitations on resources and financial constraints frequently play a pivotal role, the economic viability of digital tools assumes critical importance. The notion of "Facilitating Value" holds deep resonance in these regions, as it directly addresses the fundamental query of whether the advantages derived from embracing digital tools surpass the costs incurred. This factor surpasses mere financial deliberations, extending to a comprehensive evaluation of the potential gains, both immediate and long-term, weighed against the investments required (Harja, Y. D. et al., 2021).

The facet of reasonable pricing, an integral element of enabling value, pertains to the affordability of digital tools within the economic realities of developing nations. The accessibility of these tools at a cost that aligns with the financial capacities of individuals, institutions, and organizations becomes a pivotal determinant in their adoption (Chang et al., 2019, Kwateng et al., 2019). Within this context, stakeholders within Higher Education Institutes (HEIs) in these countries are more likely to embrace digital tools if they come at a reasonable price and promise a tangible return on investment (Madni, S. H. H. et al., 2022).

Furthermore, the concept of "Facilitating Value" encompasses the notion of value for money – a sentiment deeply ingrained in the decision-making processes of individuals and institutions alike. Digital tools that furnish comprehensive functionalities, heightened efficiency, and elevated educational experiences are perceived as valuable assets (Chang et al., 2019, Tamilmani et al., 2018). In the realm of HEIs, stakeholders are not merely concerned with cost but also with the utility and advantages that digital tools bring to their academic and administrative tasks. The perception that these tools yield a greater return in terms of enhanced educational quality, streamlined operations, and improved outcomes substantially reinforces users' intent to embrace them (Twum, K. K. et al., 2022).

Within this equation, the heightened potential of digital tools at a reduced expenditure emerges as a potent driving force. Developing and under-developed nations frequently grapple with limited resources, prompting the need for innovative solutions that maximize efficiency. Digital tools offering advanced capabilities, often at a fraction of the cost associated with conventional methods or high-end alternatives, align with the pragmatic outlook of these contexts. Stakeholders within HEIs, acutely attuned to these circumstances, are drawn to digital tools that promise significant functionality without imposing strains on already constrained budgets (Tamilmani et al., 2018).

It is important to recognize that the influence of "Facilitating Value" extends beyond immediate financial considerations. The value proposition presented by digital tools encompasses the potential to revolutionize educational approaches, enhance research endeavors, and elevate administrative processes. This, in turn, contributes to the broader objective of advancing the educational landscape within developing and under-developed nations. The convergence of reasonable pricing, value for money, and the heightened potential of digital tools at a reduced expenditure offers an enticing proposition that resonates profoundly with stakeholders within HEIs. This factor encapsulates not solely financial reflections but also the assurance of transformation and empowerment that digital tools present. As the digital revolution continues its unfolding, "Facilitating Value" emerges as a pivotal conduit that links user aspirations with the pragmatic realities of resource-restricted contexts, thereby facilitating the assimilation of digital tools and propelling the evolution of education (Chang et al., 2019, Tamilmani et al., 2018, Ain et al., 2016).

2.10 Facilitating Condition

As described in the previous section, Facilitating Condition refers to the external factors that enable or inhibit the adoption of DSC practices, such as organizational support, infrastructure, and resources. Technical support is critical to the acceptance and usage in consumer behavior, where facilitating conditions measure the level of user perception towards the adequacy of technical support and infrastructure required for utilizing innovative technologies (Briz-Ponce et al., 2016). It is a determining factor for the use of new technology, whether that is in terms of the availability of sufficient guidelines or training for first-timer users, along with proper IT support to help resolve issues during ongoing usage, so that users are encouraged and enabled to fully utilize the technology (Rahmi & Frinaldi, 2020).

Facilitating Conditions refer to the extent to which an individual perceives the presence of organizational and technical support systems to facilitate the use of a particular system. This definition encompasses concepts that are encompassed by various constructs, including perceived behavioral control, facilitating conditions, and compatibility. Each of these constructs encompasses elements of the technological and organizational environment designed to eliminate barriers to system use. There is a theoretical overlap between facilitating conditions and perceived behavioral control, incorporating facilitating conditions as a core component of perceived behavioral control within models like Theory of Planned Behavior (TPB)/ Diffusion Theory of Planned Behavior (DPTB). Compatibility, as addressed in the Innovation Diffusion Theory (IDT) framework, involves items that assess the alignment between an individual's work style and the system's utilization within the organizational context. The concept of supporting infrastructure, central to facilitating conditions, is largely encompassed by the effort expectancy construct that gauges the ease of applying the tool (Venkatesh et al., 2012; Wu and Zhang, 2018).

The findings indicate that facilitating conditions exert a direct impact on usage, extending beyond the influence explained solely by behavioral intentions. Aligning with TPB/DTPB, facilitating conditions are also modeled as a direct antecedent to usage, and this effect is expected to strengthen with experience as users discover diverse avenues of help and support within the organization, thereby mitigating obstacles to sustained usage (Venkatesh et al., 2012; Wu and Zhang, 2018).

Studies suggest that facilitating conditions play a crucial role in the adoption of new technologies in organizations (Venkatesh et al., 2012; Wu and Zhang, 2018). In the context of HEIs, facilitating conditions can refer to factors such as access to technology, training and support, and institutional policies. For example, a study by Zhang et al. (2022) found that organizational support was a critical facilitating condition that influenced the adoption of e-learning in Chinese college students. Research conducted by Sharif et al. (2019) found that the facilitating conditions factor had a significant positive effect on the intention to use a Learning Management System (LMS) among university students in Malaysia. It is a way to evaluate users' awareness of the organization's assistance and infrastructure needed to utilize the new technology (Bervell and Arkorful, 2020, Vairetti et al., 2019). The extent to which a person is convinced of a facilitating state of the system is supported by them and their degree. It helps motivate people and encourages them to use the system (Kencebay, 2019, Rallis et al., 2018). Kencebay (2019) conducted a study to examine the factors affecting the adoption of a mobile learning application using the UTAUT model. The study found that facilitating conditions were positively related to users' behavioral intention to use the application.

Similarly, Rallis et al. (2018) conducted a study on the adoption of e-learning in higher education institutions using the UTAUT model. The study found that facilitating conditions, such as access to technology and support from the institution, were positively related to users' intention to use e-learning. Since infrastructure is a critical factor in HEIs of LDCs, for their stakeholders of HEIs, its impact is certainly worth exploring for their adoption of DSC practices (International Telecommunication Union, 2020, The World Bank, n.d.).

In the realm of digital adoption, the 'Facilitating Condition' factor stands as a linchpin in shaping users' intention to engage with digital tools, particularly within the unique landscape of developing or under-developed countries. This multifaceted factor encompasses a spectrum of elements, including the availability of necessary resources, compatibility with existing devices, accessibility to help and support, and the presence of up-to-date infrastructure. These components collectively form a crucial scaffold upon which the intention to use digital tools is constructed within these specific contexts (Bervell and Arkorful, 2020, Jaradat et al., 2020).

The availability of necessary resources takes center stage in the 'Facilitating Condition' factor. In developing or underdeveloped countries, where resource limitations often cast a shadow, the accessibility of essential tools, such as computers, internet connectivity, and software, holds paramount significance. Stakeholders within Higher Education Institutes (HEIs) in these countries navigate a landscape where the absence of these resources can hinder the seamless integration of digital tools. Therefore, when these tools are made available as part of facilitating conditions, the path to their adoption becomes smoother. The presence of such resources obliterates a significant barrier and enables stakeholders to embark on the digital journey with confidence (Alalwan et al., 2018, Kwateng et al., 2019).

Compatibility with other devices represents yet another facet of the 'Facilitating Condition' factor. In a world characterized by diverse technological ecosystems, the ability of digital tools to seamlessly integrate with existing devices becomes a pivotal consideration. In developing or under-developed countries, where the spectrum of devices is often vast and varied, compatibility ensures inclusivity and extends the reach of these tools. Stakeholders within HEIs are more likely to embrace digital tools when they can be readily incorporated into their existing technological repertoire, without necessitating extensive infrastructural overhauls (Bervell and Arkorful, 2020, Jaradat et al., 2020).

The availability of help and support serves as a guiding light within the 'Facilitating Condition' factor. In these contexts, where digital literacy levels may vary, the presence of robust support mechanisms can spell the difference between hesitant adoption and confident usage. Stakeholders, particularly those within HEIs, require accessible avenues for assistance, troubleshooting, and guidance. When facilitating conditions encompass a robust support infrastructure, stakeholders are emboldened to explore and engage with digital tools, secure in the knowledge that help is readily available in their digital journey (Jaradat et al., 2020, Mukred et al., 2019).

An essential component of the 'Facilitating Condition' factor is the availability of the latest infrastructure. In developing or under-developed countries, where the digital landscape is rapidly evolving, the presence of up-to-date infrastructure forms a critical bedrock for digital tool adoption. HEIs must operate within an environment equipped with the technological backbone to support the seamless utilization of these tools. Stakeholders are more inclined to embrace digital tools when they are confident that the infrastructural foundation is in place, ensuring smooth functionality and minimizing disruptions (Garone et al., 2019, Rallis et al., 2018).

The 'Facilitating Condition' factor emerges as a crucial force that shapes users' intention to adopt and utilize digital tools within developing or under-developed countries. The amalgamation of necessary resources, compatibility, support mechanisms, and up-to-date infrastructure constructs an environment conducive to digital adoption. This factor transcends the notion of mere access; it encapsulates the readiness of the ecosystem to embrace digital tools and underscores the alignment of technology with the unique contexts of these countries. As stakeholders within HEIs navigate the digital landscape, the presence of facilitating conditions acts as a catalyst, propelling them towards a future enriched by digital engagement (Kwateng et al., 2019, Mukred et al., 2019).

2.11 Digital Literacy

Digital Literacy refers to the ability of stakeholders to use digital technologies effectively. Studies suggest that digital literacy is an important factor that influences the adoption of new technologies. In the context of HEIs, digital literacy can refer to the ability of students, faculty, and staff to use digital tools for teaching, learning, research, and administrative tasks. Digital literacy was identified as a factor for digitization in countries like Bangladesh and eventually also impact the higher education sector (UNESCO, 2018, Zelezny-Green et al., 2018).

As much as the digitization of education system in today's world can be seen as empowering for teachers and learners, but it can be also disruptive. Hence, higher level of digital literacy is a rising demand and expected from both (Alexander et al., 2017; Chan et al., 2017; Elgazzar & Elzarka, 2017). In a study by Wang and Ha-Brookshire (2018), digital literacy is reported to be a requirement for supply chain functionalities that in turn is a necessity for the preparation of Industry 4.0. It is crucial to explore the connection among various services with digital literacy (Durak & Saritepeci, 2019) and hence, the relationship between DSC practice and digital literacy in academic institution performance is also a necessity.

Aavakare, M. (2019) investigated the impact of digital literacy and information literacy on the intention to use digital technologies for learning using UTAUT2 framework. The study revealed a significant relationship between digital literacy and the intention to use digital technologies for learning. In another study by Nikou and Aavakare (2021), conducted on a Finnish university staff and students' intention to use digital technologies, found that there is a complex interrelationship between literacy skills and digital technologies among university staff and students. The study showed that information literacy has a direct and significant impact on the intention to use digital technologies. Yu et al. (2021) found mobile literacy as a moderating factor while exploring behavioral intention to use a mobile health education website in Taiwan.

Digital literacy represents the capacity to understand, access, integrate, manage, evaluate, create, and communicate information securely and correctly using digital technologies for entrepreneurship and employment (UNESCO, 2018). It is a human attribute that enables us to search, assess, share, innovate, and utilize ideas, with moral and responsibility to adopt ICT tools and technologies in combination with Internet (Reddy et al., 2021).

Higher education institutes are one of the prime advocators of leveraging this notion playing a crucial role in preparing the next generation for contributing significantly as an individual in the society (Durak and Saritepeci, 2019). Digital literacy is required by supply chain functionalities to be prepared for Industry 4.0. It is necessary to investigate if the use and impact of social media settings link to the level of literacy. Hence, it is vital to investigate the relationship between digital literacy and DSC practice settings to explore the academic institution performance in the LDCs (Wang and Ha-Brookshire, 2018).

In the rapidly evolving landscape of technological advancement, the concept of "Digital Literacy" emerges as a pivotal determinant influencing users' intention to adopt and effectively utilize digital tools, particularly within the contexts of developing or under-developed countries. This multifaceted factor encompasses a spectrum of attributes, including the ability to troubleshoot ICT-related technical issues, knowledge of digital technologies, familiarity with web-based activities, and the capability to seek support through online platforms. Each of these facets plays a substantial role in shaping users' perceptions and decisions regarding the adoption and integration of digital tools (Jaradat et al., 2020, Zhang, X. et al., 2019, Wang and Ha-Brookshire, 2018).

In the context of developing or under-developed countries, where disparities in technological accessibility and expertise persist, the significance of "Digital Literacy" becomes particularly pronounced. This factor represents a fundamental skillset that empowers individuals to navigate the digital realm with confidence and competence. It is a reflection of an individual's aptitude to harness the full potential of digital tools and effectively engage in web-based activities, transcending the mere ability to use these tools (Zhang, X. et al., 2019).

The ability to solve ICT-related technical problems constitutes a vital component of "Digital Literacy." In environments where technological resources may be limited and technical glitches are prevalent, individuals with a higher degree of digital literacy are better equipped to diagnose and resolve these issues. They possess the knowledge and skills to troubleshoot common technical challenges, minimizing disruptions and enhancing the seamless utilization of digital tools (Saritepeci, 2019, Wang and Ha-Brookshire, 2018). This is particularly pertinent in the context of developing or under-developed countries, where the availability of technical support may be scarce.

Moreover, "Digital Literacy" encompasses a profound understanding of various digital technologies. Users with a higher level of digital literacy possess the know-how to navigate through diverse digital platforms, applications, and interfaces. They are adept at harnessing the functionalities of digital tools to fulfill a range of tasks, from communication and information retrieval to collaboration and content creation. In the realm of developing or under-developed countries, individuals who are digitally literate are better positioned to leverage available resources and capitalize on the opportunities presented by digital tools (Jaradat et al., 2020, Wang and Ha-Brookshire, 2018).

Familiarity with web-based activities is another critical dimension of "Digital Literacy." Users who are well-versed in web navigation and online interactions can readily adapt to the utilization of digital tools. They are accustomed to the nuances of web interfaces, online communication, and information retrieval, enabling them to seamlessly integrate digital tools into their routines. This familiarity is of particular significance in regions where internet usage is expanding rapidly and digital platforms are becoming increasingly integral to various aspects of daily life (Durak and Saritepeci, 2019, Wang and Ha-Brookshire, 2018).

An essential aspect of "Digital Literacy" is the ability to obtain support over the Internet. Users who are digitally literate can effectively utilize online resources to seek guidance, troubleshoot issues, and enhance their understanding of digital tools. They are not reliant solely on traditional forms of technical assistance but can harness the vast repository of knowledge available through online communities, forums, and resources. In developing or under-developed countries, where access to physical support may be limited, this ability to self-source information and assistance is invaluable (Jaradat et al., 2020, Wang and Ha-Brookshire, 2018).

The "Digital Literacy" factor holds profound implications for users' intention to adopt and utilize digital tools within the context of developing or under-developed countries. Its multifaceted nature encompasses the ability to troubleshoot technical issues, familiarity with digital technologies, competence in web-based activities, and the capability to access online support. These attributes collectively empower users to navigate the digital landscape effectively, capitalize on available opportunities, and mitigate challenges. "Digital Literacy" is not merely a proficiency; it is a transformative capability that equips individuals to harness the full potential of digital tools and drives the integration of technology in regions where such skills are of paramount importance (Saritepeci, 2019, Wang and Ha-Brookshire, 2018).

2.12 Performance Expectancy

Performance Expectancy refers to the perceived usefulness and benefits of using a technology to perform a task. It is based on extrinsic motivation, job fit, and relative advantage. The extent to which the usage of advanced systems or devices can aid consumers in performing specific tasks better is the fundamental motivator for user's adapting new technology. But the perception of activities being instrumental towards achieving valuable outcomes is also an important trigger point, along with the alignment of the task at hand and the technology's capabilities that would enable users to improve job performances overall. And considering the benefits of utilizing new technology, comparatively outweighs the costs, the overall performance expectancy is met (Huang & Kao, 2015).

Performance expectancy refers to the extent to which an individual perceives that the utilization of a system will contribute to enhancing their job performance outcomes. The concepts encompassed within this construct are derived from various models, including the Technology Acceptance Model (TAM/TAM2), its amalgamation with the Theory of Planned Behavior (C-TAM-TPB), extrinsic motivation sourced from the Motivational Model (MM), job-fit as defined by the Model of Personal Computer

Utilization (MPCU), relative advantage drawn from the Innovation Diffusion Theory (IDT), and outcome expectations rooted in the Social Cognitive Theory (SCT). The potency of the performance expectancy construct lies in its capacity to predict users' intention across different scenarios, remaining consistently significant during multiple points of assessment within both voluntary and obligatory contexts (Venkatesh et al., 2012).

The construct measures how the new technology would help a user in their learning (Briz-Ponce et al., 2016) or to what extent it would perform according to users' expectations (Wairimu et al., 2019). The framework suggests that performance expectations are strong predictors of interest in the use of new technology in both voluntary and mandatory settings. Performance expectations significantly and positively impacts the utilization of information systems (Rahmi & Frinaldi, 2020). It is one of the most predominant constructs of UTAUT and UTAUT2.

Studies suggest that performance expectancy is a crucial factor that influences intention and adoption of new technologies (Wu and Zhang, 2018). In the context of HEIs, performance expectancy can refer to the perceived usefulness of DSC practices for tasks such as procurement, inventory management, and logistics. For instance, a study by Lutfi et al. (2022) found that performance expectancy significantly influenced the mobile learning technology among university students in Saudi Arab. It is a predictor that is related to the benefit that an individual expects to experience as a result of using a technology (Jaradat et al., 2020, Eneizan et al., 2019). It is the degree to which an individual believes that he or she is going to achieve an advantage in job performance using the system (Kwateng et al., 2019). It is also one of the most influential predictors of consumer's behavioral intention to adopt and use ICT. (Alalwan et al., 2018, Loureiro et al., 2018, Jakkaew and Hemrungrote, 2017, Dwivedi et al., 2017, Rana et al., 2017).

Jaradat et al. (2020) found that performance expectancy was a significant predictor of users' intention to adopt mobile health apps in Jordan. Similarly, Eneizan et al. (2019) found that performance expectancy significantly influences users' intention to adopt mobile payment technology in Saudi Arabia. Alalwan et al. (2018) also found that performance expectancy was a significant predictor of customers' intention to adopt mobile banking technology in Jordan. In the context of e-commerce, Loureiro et al. (2018) found that performance expectancy significantly influences consumers' intention to use online shopping platforms in Brazil. Jakkaew and Hemrungrote (2017) found that performance expectancy was a significant predictor of students' intention to adopt mobile learning technology in Thailand. Dwivedi et al. (2017) found that performance expectancy was a significant predictor of users' intention to adopt e-government services in India. Finally, Rana et al. (2017) found that performance expectancy significantly influences customers' intention to adopt internet banking in Pakistan.

Among the academic institutions, the performance expectancy in DSC performance is defined as how a person believes that employing the approach will assist them in accomplishing their goals (Loureiro et al., 2018, Diep et al. 2016). It is imperative that performance expectancy is a predictor for the digital supply chain stakeholders' adoption of DSC practices in the HEIs of LDCs.

The factor of "Performance Expectancy" holds a profound influence over users' intentions to embrace digital tools within the distinctive landscape of developing or underdeveloped countries. This pivotal element is rooted in the users' perception that engaging with these digital tools will culminate in a spectrum of advantageous outcomes, fundamentally elevating their overall work performance and proficiency (Faqih and Jaradat, 2021).

Within the context of developing or underdeveloped nations, where economic and technological challenges are prevalent, the significance of "Performance Expectancy" becomes even more pronounced. The allure of enhanced work efficiency, quickened task completion, elevated productivity, heightened task precision, and improved individual performance resonates strongly with users seeking to overcome the constraints imposed by limited resources and infrastructural deficiencies (Jaradat et al., 2020, Eneizan et al., 2019, Loureiro et al., 2018).

At the core of this construct lies the conviction that utilizing digital tools will substantially increase the likelihood of successfully accomplishing pivotal tasks. In environments characterized by resource constraints, time-sensitive workloads, and demanding responsibilities, the promise of improved task completion rates can significantly alleviate the burdens faced by users, contributing to enhanced work outcomes and overall job satisfaction (Jaradat et al., 2020, Kwateng et al., 2019).

Furthermore, the acceleration of task accomplishment emerges as a crucial facet of "Performance Expectancy." The rapid pace of digital tools not only enhances individual task efficiency but also bolsters collective work dynamics. In developing or underdeveloped countries, where the optimization of available resources is imperative, the ability to expedite task completion can foster a culture of agility and responsiveness, enabling organizations and institutions to navigate challenges more effectively (Jaradat et al., 2020, Kwateng et al., 2019).

The augmentation of work productivity represents another vital dimension of this factor's impact. In regions grappling with economic limitations, maximizing productivity becomes an essential strategy for sustainable growth. The prospect of digital tools enhancing work output can be a catalyst for economic advancement, providing users with the means to achieve more with the resources at hand (Eneizan et al., 2019, Loureiro et al., 2018, Salloum and Shaalan, 2018).

Moreover, the heightened accuracy of tasks facilitated by digital tools holds significant ramifications, particularly in sectors where precision is paramount. Whether in educational settings or administrative functions, the reduction of errors and inaccuracies can contribute to streamlined operations and improved outcomes, fostering a conducive environment for growth and progress (Kwateng et al., 2019, Alalwan et al., 2018).

It is worth noting that the positive impact of "Performance Expectancy" extends beyond individual tasks to encompass broader tasks and individual performance. The adoption of digital tools can lead to a ripple effect of enhanced competencies and capabilities, ultimately contributing to the upliftment of institutions, organizations, and, by extension, the entire country's developmental trajectory (Garone et al., 2019, Loureiro et al., 2018, Salloum and Shaalan, 2018).

The factor of "Performance Expectancy" serves as a transformative catalyst within the realm of digital tool adoption in developing or underdeveloped countries. By promising increased chances for task completion, accelerated task accomplishment, elevated work productivity, enhanced task accuracy, and improved individual and collective performance, this factor addresses critical needs and aspirations in resource-constrained contexts. Its influence reaches far beyond immediate tasks, fostering an environment of efficiency, effectiveness, and growth. As developing and underdeveloped nations seek to harness digital tools for progress, the resonance of "Performance Expectancy" emerges as a beacon guiding users towards a future of enhanced work capabilities and enriched outcomes (Jaradat et al., 2020, Kwateng et al., 2019, Eneizan et al., 2019, Loureiro et al., 2018, Salloum and Shaalan, 2018), Ain et al., 2016).

2.13 Trust

Trust refers to the belief that stakeholders have in the reliability, security, and privacy of the technology and the provider. Studies suggest that trust is a critical factor that influences the intention and adoption of new technologies (Jaradat et al., 2020, Almaiah et al., 2019). In the context of HEIs, trust can refer to the belief that stakeholders have in the security and privacy of their data and the reliability of the DSC practices. For example, a study by Kim et al. (2021) found that trust significantly influenced the adoption of online learning in Korean HEIs. The level of consumers reliance on the integrity of the technology that it promises to offer. Trust is an integral component for establishing and maintaining a strong digital environment. Hence, it is recognized as a cornerstone for the acceptance of new technology (Putri, 2018, Sas and Khairuddin, 2015).

Satisfaction and trust emerge as pivotal determinants in prognosticating individuals' inclination towards adopting technology. In the realm of digitization, user convictions wield a substantial influence over individuals' predisposition to engage with a specific system. The potency of Effort Expectancy (EE) and Performance Expectancy (PE), intertwined with perceived enjoyment, significantly shape the landscape of user satisfaction. Trust, a multifaceted construct, assumes varied dimensions in scholarly discourse. Arpaci (2016) encapsulated it as users' perceptions pertaining to the dependability and credibility of a system, while Alalwan et al. (2018) expanded this definition to encompass the amalgamation of trust-related beliefs—integrity, benevolence, and competence—that are intertwined with the domains of banking and mobile-based channels.

A retrospective view of prior investigations (Arpaci, 2016; Alalwan et al., 2018) reveals that students' trust levels were operationalized through their perceptions of trust-related beliefs—integrity, benevolence, and competence—specifically in the context of m-learning. Notably, the scholarly landscape remains marked by inconclusive findings concerning the impact of trust on behavioral inclination. While numerous studies have underscored the affirmative influence of trust on behavioral predisposition, certain instances have yielded disparate outcomes (Alalwan et al., 2018; Kabra et al., 2017).

Illustratively, Alalwan et al. (2018) affirmed the pivotal role of trust in shaping users' likelihood to adopt mobile technologies. Their research revealed a substantial influence of trust on users' inclination to engage with m-learning. Conversely, Kabra et al. (2017) reported an absence of a significant correlation between trust and behavioral inclination. These divergent findings illuminate the intricate interplay between trust and behavioral predisposition, accentuating the nuanced factors underpinning users' decision-making processes.

Putri (2018) conducted a study to investigate the factors influencing users’ intention to use mobile banking services in Indonesia, using the UTAUT model. The study found that trust has a significant positive effect on users’ intention to use mobile banking services. Al-Saedi et al. (2020) examined the factors influencing consumers' intention to use mobile payment, with a focus on the role of trust. The study found that trust had a significant positive impact on consumers' use intention. Akhter et al. (2020) investigated the factors influencing the intention of Bangladeshi users to adopt mobile banking services. The study found that trust significantly influenced users' intention to adopt mobile banking. Nguyen et.al. (2020) examined the factors influencing users' intention to use e-government services in Vietnam. The study found that trust significantly influenced users' intention to use e-government services.

Trust for HEI Stakeholders can be defined as their beliefs of integrity, consistency and ability that would increase their willingness to depend on DSC practices in the higher education institutes. It is broadly researched and accepted as a significant construct predicting consumer’s perception and intention toward digitization (Jaradat et al., 2020, Almaiah et al., 2019, Alalwan et al., 2018). In this context trust is stakeholders’ confidence in the reliability and worthiness of the services offered by DSC practices in HEIs of LDCs.

The paramount role of trust within the realm of technology adoption cannot be overstated. In the rapidly advancing landscape of digitalization, the factor of 'Trust' emerges as a key that profoundly shapes users' intentions to engage with digital tools, particularly within the dynamic contexts of developing or under-developed countries. This complex construct encapsulates a spectrum of dimensions, each intricately interwoven with users' perceptions, beliefs, and apprehensions surrounding digital tools (Jaradat et al., 2020, Putri, 2018).

At its core, 'Trust' signifies users' conviction in the reliability, credibility, and integrity of digital tools. It encompasses not only the belief in the functionality and efficacy of these tools but extends to encompass the broader aspects of legal safeguards and technological robustness. Users, especially within resource-constrained environments, seek assurance that their interaction with digital tools occurs within a secure and protected realm (Alamiah, M. A. et al., 2019). The factor of 'Trust' assures users of the adequacy of legal frameworks and technological infrastructures in safeguarding their interests and data, thereby mitigating concerns of potential risks and vulnerabilities (Kwateng et al., 2019).

Moreover, 'Trust' is intricately linked to the veracity of digital tools. Users must be confident in the authenticity and truthfulness of the information, resources, and functionalities provided by these tools. In contexts where access to information is pivotal, users' trust in the accuracy and reliability of digital tools plays a pivotal role in influencing their intention to engage (Kwateng et al., 2019). This element of trust becomes even more pronounced within educational settings, where students and stakeholders rely on accurate and trustworthy information to facilitate learning and decision-making.

A critical facet of the 'Trust' factor is the faith users place in the reliability of digitization as a whole. The unfolding digital revolution brings with it the promise of transformative change, but it also introduces uncertainties and disruptions. Users' belief in the overall dependability of digitization shapes their willingness to embrace digital tools for various tasks and activities. This encompasses the assurance that digital tools will consistently deliver the promised outcomes and contribute positively to users' endeavors (Alamiah, M. A. et al., 2019).

The 'Trust' factor, in its entirety, converges towards bolstering users' faith in the efficacy and potential of digitization. This faith extends to the belief that digital tools can effectively fulfill tasks, streamline processes, and enhance individual and organizational performance. Users' trust in the task-fulfillment capabilities of digital tools becomes a driving force behind their intention to engage with these tools (Jaradat et al., 2020, Almaiah et al., 2019).

Within the backdrop of developing or underdeveloped countries, where limited resources and challenges loom large, the role of 'Trust' assumes heightened significance. Users navigating these contexts seek assurances that digital tools offer a reliable pathway to overcoming constraints and enhancing efficiency. The 'Trust' factor thus emerges as a catalyst that bridges the gap between the potential of digital tools and the practical realities of users' needs (Alamiah, M. A. et al., 2019).

The 'Trust' factor serves as a cornerstone that underpins users' intentions to use digital tools in developing or under-developed countries. Its multifaceted dimensions encompass belief in digital tools, legal and technological protection, truthfulness, reliability, and task fulfillment. By fostering users' confidence in the transformative power of digitization, 'Trust' plays a pivotal role in shaping the adoption trajectory of digital tools, ultimately contributing to the advancement of education and technology within these contexts (Jaradat et al., 2020, Putri, 2018).

2.14 DSC Usage Intention

Willingness to use a particular technology for accomplishing various tasks is known as his or her behavioral intention, in this study adopted as DSC Intention. The behavioral intention of a consumer to adopt a new technology can be directly translated to his or her actual behavior. It has been meticulously proven that the behavioral intention is a dominant predictor of use behavior (Jaradat et al., 2020, Chao, 2019, Ain et al., 2016). DSC usage intention refers to the intention of the users to use digital supply chain practices. Studies have shown that user intention to adopt technology is a significant predictor of actual adoption of such practices in higher education institutions (Alharbi et al., 2020; Gómez-Ramirez et al., 2019). Under the UTAUT2 theory of behavior, the construct involves motivating factors that influence an individual's usage behavior and intention. Users are more likely to behave in a certain way if there is a strong preexisting intention to follow through. Such user behaviors are subjective, especially if the majority are more inclined to approve of it, that can be applied to analyze the adoption process for new innovative technologies. Overall, the user's perception and understanding of their habits, the price value, the hedonic motivation, facilitating conditions, social influence, performance, and effort expectancy, altogether positively impact the users' acceptance and ultimately, usage of technology (Chaveesuk et al., 2022).

Moreover, In the research conducted by Hammouri et al. (2021), the authors found that usage intention mediates the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions with use behavior. The study was conducted in the context of mobile payment adoption in China. Another study by Parayil et al. (2022) examined the mediating effect of usage intention on the relationship between trust and use behavior and found that usage intention partially mediates this relationship. The study was conducted in the context of mobile banking adoption in Maldives. The research conducted by Hafez and Amanullah (2021) investigated the mediating effect of usage intention on the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit with use behavior. The study was conducted in the context of mobile banking adoption in Bangladesh.

In a study by Wu et al. (2022), the authors found that usage intention mediates the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation with use behavior. The study was conducted in the context of mobile health application adoption in Iran. The research conducted by Fatima et al. (2021) examined the mediating effect of usage intention on the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit with use behavior. The study was conducted in the context of mobile payment adoption in Pakistan.

The principle of trust activity is a broad word to enable credible evidence that an academician is likely to take a specified action towards DSC Practices. There has been empirical evidence that the direct effect of intention on technology is significantly positive (Chao, 2019).

Al-Saedi et al. (2020) carried out research aimed at identifying the predominant elements that expanded upon the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of the adoption of Mobile payment (M-payment). This study employed a quantitative meta-analysis methodology. The study revealed that factors such as perceived risk, perceived trust, perceived cost, and self-efficacy emerged as the most recurrent elements that exhibited notable outcomes in the surveyed research. The data was gathered from a total of 436 users of M-payment services in Oman. The outcomes of the study demonstrated that the most influential predictor of users' intention to utilize M-payment systems is performance expectancy, succeeded by social influence, effort expectancy, perceived trust, perceived cost, and self-efficacy, in that order.

Adopting an expanded version of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, an examination was carried out on a cohort of 100 individuals belonging to Generation Z in Jakarta and its environs. The objective was to delve into the predisposition to utilize mobile payment methods. The findings indicated that elements encompassing Performance Expectancy, Social Influences, Facilitating Condition, Perceived Enjoyment, and Trust exert a substantial impact on the inclination to engage in the use of mobile payments during online transactions. Conversely, Effort Expectancy was not found to exert a noteworthy influence (Nur, T. and Panggabean, R. R. 2021).

Abbad (2021) applied the unified theory of acceptance and use of technology (UTAUT) as a framework to examine the inclination of students to adopt and their effective utilization of Moodle, an electronic learning system, within a public university situated in a developing country, namely Jordan. The study delved into four primary factors influencing intention and utilization: performance expectancy, effort expectancy, social influence, and facilitating conditions. The outcomes demonstrated that performance expectancy and effort expectancy influenced the students' intentions to engage with Moodle, whereas social influence did not exhibit a significant impact. Moreover, the findings confirmed the direct correlation between behavioral intentions and facilitating conditions in relation to students' utilization of Moodle.

A study was also carried out by Alblooshi, S. A. (2021) to explore the immediate impact of the four key factors influencing the adoption of e-learning, including the supplementary factor of service quality, on the behavioral inclination of higher education institution (HEI) students to utilize e-learning technologies within the UAE. Additionally, Alblooshi examined the intermediary function of perceived satisfaction, behavioral intention, and perceived usefulness in the connection between the five factors influencing e-learning adoption and the effective usage of e-learning systems. Employing quantitative methodology and adopting a survey research design, data were collected from a participant pool of 453 students drawn from pioneering universities in the UAE equipped with e-learning infrastructure. The findings reveal that perceived usefulness and perceived satisfaction effectively mediate the relationship between performance expectancy, effort expectancy, social influence, service quality, facilitating condition, and the concrete usage of e-learning. However, students' behavioral intention solely acts as an intermediary between facilitating condition and the practical use of e-learning, whereas it does not serve as a mediator for the link between performance expectancy, effort expectancy, social influence, service quality, and e-learning adoption. Intriguingly, the study underscores the pivotal role of service quality in shaping HEI students' perceptions of the usefulness and satisfaction derived from utilizing e-learning technologies.

In another research study it was investigated how students at Universiti Kebangsaan Malaysia (UKM) were adopting the use of MOOCs. The study's findings were derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The results indicated that factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions played a role in influencing the students' decision to use MOOCs for their learning. This research highlighted that the UTAUT factors examined in this study had a significant impact on students' behavioral intention to utilize MOOC technology (Haron, H. et al., 2021).

In accordance with the findings, therefore, DSC usage intention of stakeholder in the HEIs to adopt DSC is certainly a determinant for future usage of the DSC practices in the academia of LDCs and also for its mediating effect on the factors that influences DSC usage intention among the stakeholders. By understanding DSC usage intention, organizations can better position themselves to adopt and implement new digital supply chain practices. As evident that various researchers have explored the factors that impacts users’ intention of adopting new technology in numerous domains. A user who believes that DSC will improve their performance, DSC is easy to use, resources and supports are available, entrust on DSC practices, and also it is worth spending the value, is more likely to have a strong DSC usage intention.

2.15 DSC Practice

Tasks relevant to the digitization of the network among an organization and its suppliers for producing and distributing products or services. DSC practices are geared towards a value-driven and intelligent network that facilitates new ideas and approaches with technology and analytics that foster the generation of revenue and add business value (Rasool et al., 2021, Büyüközkan and Göçer, 2018).

Research by Kao et al. (2019) aimed to investigate the relationship between user's intention and use behavior to adopt a IoT-based wearable system using UTAUT2 and the results of the study showed the positive relationship between user's intention and use behavior. The study by Wu and Liu (2022) explored the factors influencing the adoption of mobile payment apps using UTAUT2. The findings revealed that user's intention have a positive influence on their actual use behavior of mobile payment apps. Research by Alshammari et al. (2021) aimed to investigate the factors influencing the adoption of e-health management in Saudi Arabia using UTAUT2 and found that user's intention positively influences their actual use behavior.

Chao, C. M. (2019) studied consumers' inclination to engage with m-learning, utilizing an extended version of the unified theory of acceptance and use of technology (UTAUT) model. This extended model incorporated additional factors such as perceived enjoyment, mobile self-efficacy, satisfaction, trust, and perceived risk as moderators. The findings demonstrated that several factors significantly and positively influenced behavioral intention. Notably, satisfaction, trust, performance expectancy, and effort expectancy played crucial roles in shaping behavioral intention. Additionally, perceived enjoyment, performance expectancy, and effort expectancy exhibited positive connections with behavioral intention. Mobile self-efficacy showcased a notably positive impact on perceived enjoyment, while perceived risk played a moderating role by negatively affecting the relationship between performance expectancy and behavioral intention.

In a separate research endeavor aimed at investigating the intentions and actions of Indonesian customers towards using mobile banking (m-banking), it was noted that while the impact of performance expectancy on behavioral intention proved to be insignificant, the effect of effort expectancy demonstrated a positive and noteworthy significance. The influence of social influence on the intention to adopt m-banking was found to be inconsequential, yet the effect of facilitating conditions was established as positive and significant. Furthermore, the study established a significant and positive connection between behavioral intention and usage behavior. This study shed light on the factors that drive the intention and behavior of urban millennials in Indonesia towards adopting m-banking. Among these factors, effort expectancy and facilitating conditions emerged as the primary determinants. The urban millennial generation displayed a more individualistic orientation rather than a collectivist one. Notably, the influence of social factors did not play a relevant role in their awareness of the benefits of m-banking usage. Their utilization of m-banking was primarily directed towards individual and daily activities rather than work-related tasks, rendering performance expectancy a less influential factor in their adoption of m-banking (Purwanto, E., and Loisa, J., 2020).

In numerous research conducted in the Higher Education Institutes, the researchers observed significant correlation among the usage intention and use behavior among the users while adopting new technologies. Like, Abbad (2021) applied UTAUT as a framework to observe the adoption of Moodle among students of Jordan and revealed that along with four primary factors influencing intention and utilization, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions, the usage intention also impacts student ultimate use behavior. In a study to explore how students at a Malaysian university were adopting the use of MOOCs, it was found that that the factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions played a role in influencing the students' decision to use MOOCs for their learning. This research also highlighted that students' behavioral intention to utilize MOOC technology is also (Haron, H. et al., 2021). Alblooshi, S. A. (2021) also explored the adoption of e-learning in the higher education institutes of UAE and identified students' behavioral intention solely acts as an intermediary between facilitating condition and the practical use of e-learning, whereas it does not serve as a mediator for the link between performance expectancy, effort expectancy, social influence, service quality, and e-learning adoption.

DSC practice refers to the actual use of digital supply chain practices in higher education institutions. Recent research has shown that factors such as facilitating conditions, performance expectancy, and digital literacy significantly influence the adoption and use of digitalization practices in higher education institutions (Nikou & Aavakare 2021, Aavakare, M., 2019).

The degree of a stakeholder's adoption of Digital Supply Chain (DSC) in the higher education institute is defined as DSC practice in this study as adapted from the UTAUT2 model. DSC practice is capable of widespread availability of information, efficient collaboration and communications using digital platforms, which eventually results in increased agility, reliability and transparency among the stakeholders, (Saengchai and Jermsittiparsert, 2019, Büyüközkan and Göçer, 2018), in this study as adopted in the framework to study the HEI stakeholders of LDCs.

Table 2.16 summarizes the extracted elements, their appropriate predictor items which are utilized to develop the conceptual framework in this study, and their sources of adoption found in prior research.

Table 2.16

Summary of the Extracted Factors, their applicable predictor items used in this study and source of adoption

Item of Each Factor	**Author (Year)**
Facilitating Value	
Reasonable price of digital tools	Chang et al. (2019), Kwateng et al. (2019), Alalwan et al. (2018),
Used digital tools are good value for the money	Chang et al. (2019), Tamilmani et al. (2018), Ain et al. (2016)
Latest price of digital tools is justified	Chang et al. (2019), Alalwan et al. (2018)
High capability of DSC tools is availed with minimum cost	Ain et al. (2016), Tamilmani et al. (2018)
Value of Digital Supply Chain tools worth the price	Alalwan et al. (2018), Tamilmani et al. (2018)

Table 2.16 continued

Item of Each Factor	Author (Year)
Facilitating Condition	
Availability of necessary resources to use digital platform	Bervell and Arkorful (2020), Jaradat et al. (2020), Mukred et al. (2019)
Availability of necessary knowledge to use digital platform	Alalwan et al. (2018), Kwateng et al. (2019), Mukred et al. (2019)
Compatibility of digital tools with other personal devices used	Bervell and Arkorful, (2020), Jaradat et al. (2020)
Availability of ICT support	Jaradat et al. (2020), Mukred et al. (2019)
Availability of up-to-date version of digital infrastructure	Garone et al. (2019), Rallis et al. (2018)
Digital Literacy	
Ability to solve ICT related technical problem	Saritepeci (2019), Wang and Ha-Brookshire (2018)
Knowledge of digital technologies	Jaradat et al. (2020), Wang and Ha-Brookshire (2018)
Familiarity web-based activities	Durak and Saritepeci (2019), Wang and Ha-Brookshire (2018)
Ability to obtain support over the Internet	Jaradat et al. (2020), Durak and Saritepeci (2019)
Trust	
Belief on the implementation of DSC practice	Jaradat et al. (2020), Putri (2018), Kwateng et al., (2019)
Assurance of adequate protection using the DSC Practice in legal and technological structures	Almaiah et al. (2019), Kwateng et al. (2019)
Truthfulness of DSC Practice	Jaradat et al. (2020), Putri (2018)
Faith on the reliability of DSC practice	Jaradat et al. (2020), Almaiah et al. (2019)

Table 2.16 continued

Item of Each Factor	Author (Year)
Belief on the fulfillment of tasks using DSC practice	Jaradat et al. (2020), Putri (2018)
Performance Expectancy	
Adoption of DSC practice increases chances the completion of important work	Jaradat et al. (2020), Eneizan et al. (2019), Loureiro et al. (2018)
Usage of DSC Practice quickens tasks accomplishment	Jaradat et al. (2020), Kwateng et al., (2019)
Increase of work productivity using DSC practice	Eneizan et al. (2019), Loureiro et al. (2018), Salloum and Shaalan (2018), Ain et al. (2016)
Increase of tasks accuracy using DSC practice	Kwateng et al., (2019), Alalwan et al. (2018)
Enhancement of task and individual's performance using DSC practice	Garone et al. (2019), Loureiro et al. (2018), Salloum and Shaalan (2018)
Digital Supply Chain Intention	
Willingness to use DSC practice regularly	Chao (2019), Ain et al. (2016)
Realization of DSC Practice need	Chao (2019), Garone et al. (2019),
Belief of increased productivity using DSC practice	Chao (2019), Garone et al. (2019),
Continuity of DSC practices in future tasks	Jaradat et al. (2020), Garone et al. (2019)
Adaptability DSC practices	Jaradat et al. (2020), Garone et al. (2019)
Digital Supply Chain Practice	
Adopting DSC Practice	Rasool et al. (2021), Ain et al. (2016)
Agreement with the DSC practices to enables quicker accomplishment of tasks.	Saengchai and Jermsittiparsert (2019), Garone et al. (2019)
Ascertain belief on DSC to increase job productivity	Jaradat et al. (2020), Kwateng et al., (2019)

Table 2.16 continued

Item of Each Factor	Author (Year)
Agree that DSC practice is dependable	Kwateng et al. (2019), Ain et al. (2016)
Belief that DSC practice increases creativity and innovation	Büyüközkan and Göçer (2018), Garone et al. (2019)

2.16 Hypothesis Development

Based on the conceptual framework of the factors influencing HEI stakeholders use intention and use behavior in adopting DSC Practices in Bangladesh, as illustrated in figure 2.8 deduced from the literature discussed in the previous section on the digital supply chain in higher education institutes, relevant theoretical model of user acceptance of digitization – Unified Theory of Acceptance and Use of Technology and digital literacy, the hypotheses to be studied are presented in the following sections.

Hypothesis 1 is based on the factors that prescribe the intention of Digital Supply Chain (DSC) usage among HEI stakeholders in Bangladesh and their relationship with user intention.

i. Digital Literacy and DSC Usage Intention

Digital literacy (DL) is the degree of understanding and level of knowledge of the technology of a user. Findings from the literature review suggest that technology recognition involves the behavioral purpose of the HEI stakeholders in the least developed countries like Bangladesh. Based on results from Queiroz and Wamba (2019), technological knowledge affects the meaning of actions to implement in higher educational institutions in such countries. Literature found in empirical research has confirmed the apparent influence of behavioral intention on constructive technology perception (Alaeddin & Altounjy, 2018). As illustrated in section 2.8.3, studies conducted by numerous researchers, like, Hasan et al. (2022) on the adoption of mobile banking in Pakistan, Arpaci and Basol (2020) on the adoption of e-learning in Turkey, found that digital literacy has a positive and significant effect on users' intention to adopt digital technology. All these studies highlight the importance of digital literacy as a key factor influencing technology adoption.

As per the data found in the reports of the United Nations and International Telecommunication Union, it was evident that there are many aspects that contributes to the digitization drawback in countries like Bangladesh and digital literacy is one of the prime ones among these aspects, particularly, at the individual stakeholder level. The more intellectually users find themselves improved in digital literacy, the more they engage in behavioral purposes. The researcher, therefore, constructs the following hypothesis:

> ***$H1_A$:*** *Digital literacy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.*

ii. Facilitating Condition and DSC Usage Intention

The concept of facilitating condition (FC) is a grade at which a person assumes that a regulatory and technological infrastructure influences the intention of stakeholders' intention to use DSC in higher education institutes. Observational research also shows a favorable impact of facilitating conditions towards the technology usage intention. As expressed in section 2.8.2, studies conducted by Zhang et al. (2022) on the adoption of e-learning among college students in China, by Sharif et al. (2019) on the use of Learning Management System (LMS) among university students, Al-Adwan et al.

(2018) on the adoption of a mobile learning application using the UTAUT model found that facilitating conditions were positively related to users' behavioral intention. Ensuring adequate support facilities for an academician would establish DSC even more effectively. Therefore, facilitating condition has impact on the behavioral purpose of the DSC usage in HEIs of Bangladesh. Therefore, the following hypothesis is suggested by the researcher:

> ***H1$_B$:*** *Facilitating conditions positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.*

iii. Facilitating Value and DSC Usage Intention

Facilitating Value (FV) is adapted from Price Values, one of the initial constructs of the UTAUT2 framework, which, in education sector usually refers to the expense that students, faculty members, administrators, and other stakeholders spend for mobile devices, hardware, software, or data packages. Previous studies established the fact that justified expense of technology positively impacts users' technology usage intention. Even though many of these costs are covered by the organization and would not directly affect the users, some researchers identified that the 'Price Value' may not materialistically affect the behavioral intention (Hu et al., 2020). But the users' perception of these costs is expected as the value of facilities. As illustrated in Section 2.8.1, studies conducted by Alharbi et al. (2020) on the adoption of cloud-storage technologies in Malaysian HEIs, Chang et al. (2019) on the adoption of mobile payment services, c et al. (2019) on the acceptance of mobile banking services have observed that consumers' willingness to accept and adopt new technology is significantly affected by the facilitating value. Facilitating Value has a significant positive effect on users' intention to adopt and use technology. Hence, this research considers the construct as facilitating value than actual price value. The study will demonstrate the stakeholders' understanding of the perceived facilitating value supporting the education institutional. Therefore, following hypothesis is suggested by the researcher:

$H1_C$: *Facilitating value positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.*

iv. Performance Expectancy and DSC Stakeholders' Intention

Performance Expectancy (PE) refers to how much an individual expects that the use of the device can contribute to achieving better performance at work (Dhiman et al., 2019 and Venkatesh et al., 2003). This study relates to the anticipated success of the degree to which the users' belief would increase the efficiency and performance of the DSC's usage intention in the HEIs of Bangladesh. The acceptance and use of emerging technology in the DSC intention is related to human motivation through the level of performance. Thus, performance creates high expectations and institute's efficiency in the educational organizations. In section 2.8.4 it was described that numerous researchers, like, Lutfi et al. (2022) on the adoption of m-learning in Saudi HEIs, Jaradat et al. (2020) on the adoption of mobile health apps in Jordan found that performance expectancy significantly influenced the adoption of technology. Eneizan et al. (2019) on users' intention to adopt mobile payment technology in Saudi Arabia found that performance expectancy was a significant predictor of users' intention to adopt new technology. Similarly, in the context of e-commerce, Loureiro et al. (2018) found that performance expectancy significantly influences consumers' intention to use online shopping platforms in Brazil, and like Jakkaew and Hemrungrote (2017) found a similar result in the adoption of mobile learning technology in Thailand. Dwivedi et al. (2017) and Rana et al. (2017) also found that performance expectancy was a significant predictor of users' intention to adopt e-government services in India and Internet banking in Pakistan, respectively. The decision of individuals to use and implement technologies depends greatly on the projected success (Alalwan et al., 2016; Venkatesh et al., 2012; Venkatesh & Zhang, 2010; Venkatesh et al., 2003). Academicians choose to adopt emerging technologies more often if they feel such inventions are more advantageous and valuable in their everyday lives. Performance was already well-known as a more effective means to give universal access to a range of services for academicians in the HEIs. Therefore, following hypothesis is suggested by the researcher:

> ***$H1_D$:*** *Performance Expectancy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.*

v. Trust and DSC Stakeholders' Intention

Trust (T) can vary according to expectations from one to another. This study pointed to the need for institutional development in higher education to be exposed and mutually supportive. In the context of least developed countries like Bangladesh, trust is an essential component for the stakeholders of HEIs. Furthermore, it is important to consider the ramifications of trust in many contexts, especially to recognize the model of technology design in academia. For example, in order to conduct operations, an information-sharing link is required. However, the trust and DSC usage intention between participants generally have little responsibility, which is a significant challenge for organizations. As illustrated in section 2.8.5 earlier, many researchers observed trust significantly influences user's intention to adopt new technology, like Kim et al. (2021)'s research on the adoption of online learning in Korean HEIs, Putri (2018)'s investigation on mobile banking services in Indonesia, Al-Saedi et al. (2020)'s study on mobile payment, Akhter et al. (2020)'s research on Bangladeshi users to adopt mobile banking services. The level of consumers' reliance on the integrity of the technology it promises to offer, trust is an integral component for establishing and maintaining a strong digital environment. DSC usage intention also boosts the trust levels of supply chain participants, as recent research on the digital market in the academic industry suggests (Putri, 2018). Eventually, the researcher constructs the hypothesis below:

> ***$H1_E$:*** *Trust positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh.*

Hypothesis 2 is based on the association between the user intention and practice of Digital Supply Chain (DSC) among HEI stakeholders in Bangladesh.

vi. DSC Stakeholders' Intention and DSC Practice

DSC usage intention means the extent to which an individual will deliberately commit to or not be a part of the potential DSC practices. The DSC intention to practice implies the integration of the DSC factors in the academia that influences the stakeholders to adopt DSC Practice in the HEIs. It also seeks to boost operations and use this DSC practices to change the environment of HEIs in Bangladesh by unlocking it with new opportunities of digitalization adaptation. The practices of DSC are keen to monitor usability, reduce financial requirements, and ensure digital business data sharing. It is also recommended that the academic industry constantly evaluates and updates its policies to understand and accommodate the effect of DSC practices among its stakeholders. Finally, it also can increase the knowledge and awareness of the emerging DSC practice in academia. Hence, the academia community must then take the facility and usefulness of DSC. The researcher, therefore, found that the intention and practices influence DSC usage is significant to be studied in this research. It was illustrated in section 2.8.7 earlier user's intention positively impact user's adoption of new technology. Numerous researchers have investigated and found the same result, like, Wu and Liu (2022)'s research on adoption of mobile payment, Alshammari et al. (2021)'s study on the adoption of e-health management in Saudi Arabia, Kao et al. (2019)'s research on IoT based wearable fitness tracker using UTAUT2. Therefore, the researcher suggests the following hypothesis:

> ***H2:*** *Digital Supply Chain usage intention positively affects the Digital Supply Chain practices of the HEI stakeholders in Bangladesh.*

Hypothesis 3 is based on the mediating effect of stakeholders' use intention on the relationship between each of the factors – Digital literacy (DL), Facilitating conditions (FC), Facilitating value (FV), Performance Expectancy (PE) and Trust (T) Digital and of Digital Supply Chain (DSC) practices among Bangladesh's HEI stakeholders.

vii. Medicating effect of the DSC Use Intention on the factors towards DSC Practice

As described in section 2.8.6 earlier, research conducted by numerous researchers have observed significant mediating effect of the usage intention on the factors that influences users' use behavior while accepting a new technology. Like, Hammouri et al. (2021)'s study of mobile payment adoption, Parayil et al. (2022)'s research on mobile banking adoption in Maldives, Karim et al. (2019)'s investigation on mobile banking adoption in Bangladesh, Abadi et al. (2021)'s study on mobile health application adoption in Iran. All of these researchers observed the full or partial mediating effect of user intention on the factors that influence them to adopt new technologies. Same evidence was also observed in the researchers conducted by Fatima et al. (2021) when they examined the mediating effect of usage intention on the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit with use behavior in the context of mobile payment adoption in Pakistan.

Based on the underpinning theory UTAUT2 and the research literature findings another hypothesis is also established as following:

> ***$H3_A$:*** *Relationship of Digital literacy (DL) the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh.*
>
> ***$H3_B$:*** *Relationship of Facilitating conditions (FC) with the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh.*
>
> ***$H3_C$:*** *Relationship of Facilitating value (FV) with the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh.*
>
> ***$H3_D$:*** *Relationship of Performance Expectancy (PE) with the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh.*
>
> ***$H3_E$:*** *Relationship of Trust (T) with the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh.*

2.17 Partial Least Squares Structural Equation Modeling (PLS-SEM)

Partial Least Squares Structural Equation Modeling (PLS-SEM; also called PLS path modeling) is a type of Structural Equation Modeling (SEM). It is a second generation is a multivariate data analysis method. In multivariate data analysis, multiple variables that represent measurements associated with events, individuals, situations, organizations, activities, etc. are simultaneously analyzed using the application of statistical methods. SEM is applied to either confirm or explore theory. Exploratory modeling is used for constituting theory, while confirmatory modeling is for testing theory. PLS-SEM is variance-based structural equation modeling and is mostly adopted by researchers for development of theories through exploratory research (Hair Jr et al., 2021).

PLS Path models display variable relationships and the hypotheses in diagram format as examined by applying structural equation modeling. There are 4 (four) base elements of developing path models. They are, (1) constructs, (2) measured variables, (3) relationships, and (4) error terms. The first item, constructs, also known as unobserved variables, are basically latent variables that cannot be directly measured, represented as circles or ovals in path models. Measured variables or manifest variables are directly measured observations from raw data, also commonly known as indicators. They are found in rectangles in path models. Single-headed arrows are used to model the relationships which also represent hypotheses in path Models. They also indicate a predictive/causal relationship. In the estimation of path models, the unexplained variance for endogenous constructs, and reflectively measured indicators are represented by error terms. Error terms are not present in the case of exogenous constructs and formative indicators.

Moreover, path models are also distinguished by the “structural (inner) model” and the “measurement (outer) models”. When developing a structural model, the role of the theory is important. Theory is based on systematically and scientifically developed hypotheses that predict and explain outcomes. On the other hand, measurement theory identifies the process of modeling unobservable latent variables (constructs). Latent variables can be classified as either endogenous or exogenous. Relationships among the unobservable variables are shown by structural theory. The first step in evaluating PLS-SEM results involves the assessment of the measurement models. After the measurement models meet all required criteria, then the structural model needs to be measured and tested (Hair et al., 2017, Sarstedt et al., 2017).

It is not only for exploratory research the PLS-SEM is appropriate, it can be also used for confirmatory research (Hair et al., 2017). Like most other statistical methods, there are guidelines to evaluate PLS-SEM model results (Hair et al., 2017). Depending on the context, this evaluation criteria and guidelines may vary. It is necessary to evaluate the measurement model in terms of a number of different parameters (Cheah et al., 2018).

2.17.1 Evaluation of Measurement (Outer) Model

To evaluate the standardized outer loadings of the observed variables, the reliability of each of its indicator's variance is observed as it implies that the variance is explained by the latent design. It is accepted when the observed variables have more than 0.7 value of outer loading and value less than 0.4 is discarded. In the case of exploratory research, a value of 0.4 or higher is acceptable (Hair et al., 2017; Wong, 2013, Hair et al., 2011). Composite Reliability value is usually used because it has better assessment capability of internal consistency (Jin & Wang, 2019; Hair et al., 2017; Peterson & Kim, 2013). The value of composite reliability should be 0.7 or higher with an exception for exploratory research, where 0.6 or higher is also acceptable (Hair et al., 2017).

A model is considered to be valid if the level of positive associations between variables within the same model is high (Jin & Wang, 2019). A suitable measure to assess the convergent validity of the measurement model is known as Average Variance Extracted (AVE) value, which should be 0.5 or higher (Jin & Wang, 2019; Hair et al., 2017; Henseler, 2017).

According to Fornell and Larcker (1981) the “square root” of AVE of each latent variable must be greater than the correlations among the latent variables which means all construct pairs satisfy the criterion (Ab Hamid et al., 2017). The square root value of each construct’s AVE measurement must be more than its highest correlation with any of the other constructs. The idea behind Fornell-Larcker is that a construct possesses higher variance with its own associated indicators compared to others.

Some researchers also find heterotrait-monotrait ratio (HTMT) as more appropriate in identifying the discriminant validity when the value of HTMT is lower than 0.85 (threshold value). HTMT is calculated from the mean of all correlations among the indicators across the constructs measuring different constructs relative to the mean of the average correlations among the indicators measuring the same construct (Hair et al., 2017; Goodhue et al., 2012; Henseler et al., 2009).

2.17.2 Evaluation of Structural (Inner) Model

Once the outer measurement model was confirmed valid and reliable, the researcher needs to evaluate the inner structural model. This part included the analysis of observing the model's predictive relevancy and the relationships between the constructs. The statistical test-based evaluation criteria of this section are described below:

Variance inflated factor (VIF) can be measured to investigate the presence of multicollinearity among the exogenous latent variables. VIF greater than five has been shown by Hair and colleagues (Hair et al., 2017) to imply the presence of multicollinearity. The structural model VIF values for the exogenous component must be less than the cut-off values for the components (Hair et al., 2017). Whenever an independent variable has a high correlation with one or more other independent variables in case of a multiple regression equation, the value of multicollinearity increases. Multicollinearity becomes an issue since it weakens the significance of an independent variable statistically. (Hair et al., 2017)

One of the most commonly used measures to evaluate the structural model is the coefficient of determination (R^2 value). It measures model's predictive power by calculating the squared correlation among a specific endogenous construct's actual and its predicted values. The combined effect of the exogenous latent variables on the endogenous latent variable is represented by this coefficient. In the structural model, the coefficient of determination aims to measure the overall effect and variance explained in the endogenous construct. It is a measure of the model's predictive accuracy (Hussain et al., 2018). Hair et al. (2013) stated that the value of R^2 more than 0.75 is substantial, 0.50 is moderate, 0.26 is weak.

The significance of the hypothesis is tested using the β value. The greater the beta coefficient (β), the stronger the effect of an exogenous latent construct on the endogenous latent construct, hence, signifies the associated hypotheses. The significance of the β value needs to be verified using the T-statistics test. Bootstrapping test checks the t-value > 1.96 (for 2-tailed) which is equivalent to $p < 0.05$ (Sarstedt et al., 2015).

Along with evaluating the R^2 values of endogenous constructs, when a specified exogenous construct is omitted from the model, the change in the R^2 value can be used to evaluate whether there is impact of omitted construct on the endogenous constructs. Basically, the variation of the R^2 values is measured by estimating the PLS path model two times. First time, including the exogenous latent variables, and the second time with the exclusion of exogenous latent variables. Schloderer et al. (2014) suggested the values level of effect size, i.e., f^2 as 0.35 should be taken as large, 0.15 as medium, and 0.02 as small among the model constructs respectively (Hair et al., 2017).

The Predictive relevance of the model (Q^2) values measure how strongly the path model can forecast the observed initially values, which is calculated using blindfolding procedures. Q^2 the criterion in this part can be recommended to predict the endogenous latent construct using the conceptual model (Tenenhaus et al., 2005). Q^2 shows how well the empirically collected data can be reconstructed using PLS parameters and the model. Q^2 must be greater than 0.5 for endogenous latent constructs to be relevant and adequate (Hair et al., 2017).

To validate a model that describes empirical data, an index for a complete and appropriate model should be used and it is known as Goodness-of-Fit (GOF). The values of GOF falls between 0 and 1. The values measured more than 0.36 largely indicates the global validation of the path model in PLS-SEM (Hussain et al., 2018). Other than that, the value 0.25 is considered as a medium, and 0.10 is considered as small. The GoF is calculated by the formula of the square roots of the average mean of R^2 multiple by AVE and the model GoF (Hair et al., 2017). A model fit measure is the Standardized Root Mean Square Residual (SRMR). It measures the root mean square discrepancy among the model-implied correlations and the observed correlations. Hair et al. (2017) said the value SRMR that less than 0.08 are considered a good fit for the model development using PLS-SEM. Normed Fit Index (NFI) analyzes the discrepancy between the chi-squared value of the hypothesized model and the chi-squared value of the null model. NFI results in values between 0 and 1. Hair et al. (2021) stated that the more the value of NFI is closer to 1, the more the model will be fit. Usually, the NFI values above 0.9 represent an ideal condition of acceptable fit. The expected correlations among the observed variables with different latent variables where the values of correlation coefficient lie between 0 and 1 (Hair et al., 2017). Higher statistical power the PLS-SEM is very useful for exploratory research that examines underdeveloped or on-going developing theory. Greater statistical power also means that PLS-SEM is expected to identify relationships more significantly when they are undoubtedly present in the population (Sarstedt and Mooi, 2019).

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) and Partial Least Squares Structural Equation Modeling (PLS-SEM) were used by many researchers in the education domain. Jaradat et al. (2020) applied them to study the adoption of Cloud Computing in Higher Educational domain, Bervell and Arkorful (2020) researched utilization of LMS-enabled blended learning in distance higher education, Almaiah et al. (2019) explained the University Students' Acceptance of Mobile Learning System, Ahmad et al. (2020), Salloum and Shaalan (2018) explored factors affecting students' perception of E-Learning system in universities. Chao (2019) in his studies studied factors influencing the behavioral intention of users towards mobile learning, Mukred et al. (2019) researched factors in adopting an Electronic Records Management System in the Educational Sector, Mosunmola et al. (2018) studied adoption and usage of Mobile Learning in universities. Thongsri et al. (2018) also explored behavioral intention towards usage of M-learning and Ain et al. (2016) studied the influence of learning value on learning management system.

2.18 Summary of Chapter

Based on a thorough review of numerous latest and contemporary literatures relevant to the objectives of the research, a suitable conceptual research framework is built. The hypotheses of this study were then presented based on the literature studied. The framework is going to be the skeleton of the further analysis in this study integrated with the appropriate methodology as evidenced in the previously conducted studies on similar research.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The objective of this chapter is to present a complete overview of the methodologies used for the analysis purpose in this research, i.e., to develop a model of digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh representing least developed countries. In total, there are 9 (nine) sections in this chapter. Section 3.2 presents the research design, including the overview of the research process. Then, from Section 3.3 until Section 3.7, they describe the research process adopted in this study, which is eventually divided into four phases and the summary of the whole research process is explained in Section 3.8. Finally, the summary of this chapter is presented in Section 3.9.

3.2 Research Design

In the first phase of this quantitative research, the descriptive design approach was applied to explore the Digital Supply Chain (DSC)'s general practices in the domain of Higher Education Institutes (HEIs). Then, one of the most important parts of this research is the second phase, where a conceptual model of the DSC's general practices for HEI has been constructed. In this second phase, exploratory research design was applied where the problems and issues from the previous studies were discovered, and this research filled the gap of those previous studies by constructing the conceptual model. In the phase three a survey was conducted among the randomly selected stakeholders of HEIs of Bangladesh using a questionnaire. Later in phase four, strength and relationships among the factors of the conceptual model were identified using PLS-SEM model regarding their HEI stakeholders' perception of DSC usage intention and practices in Bangladesh.

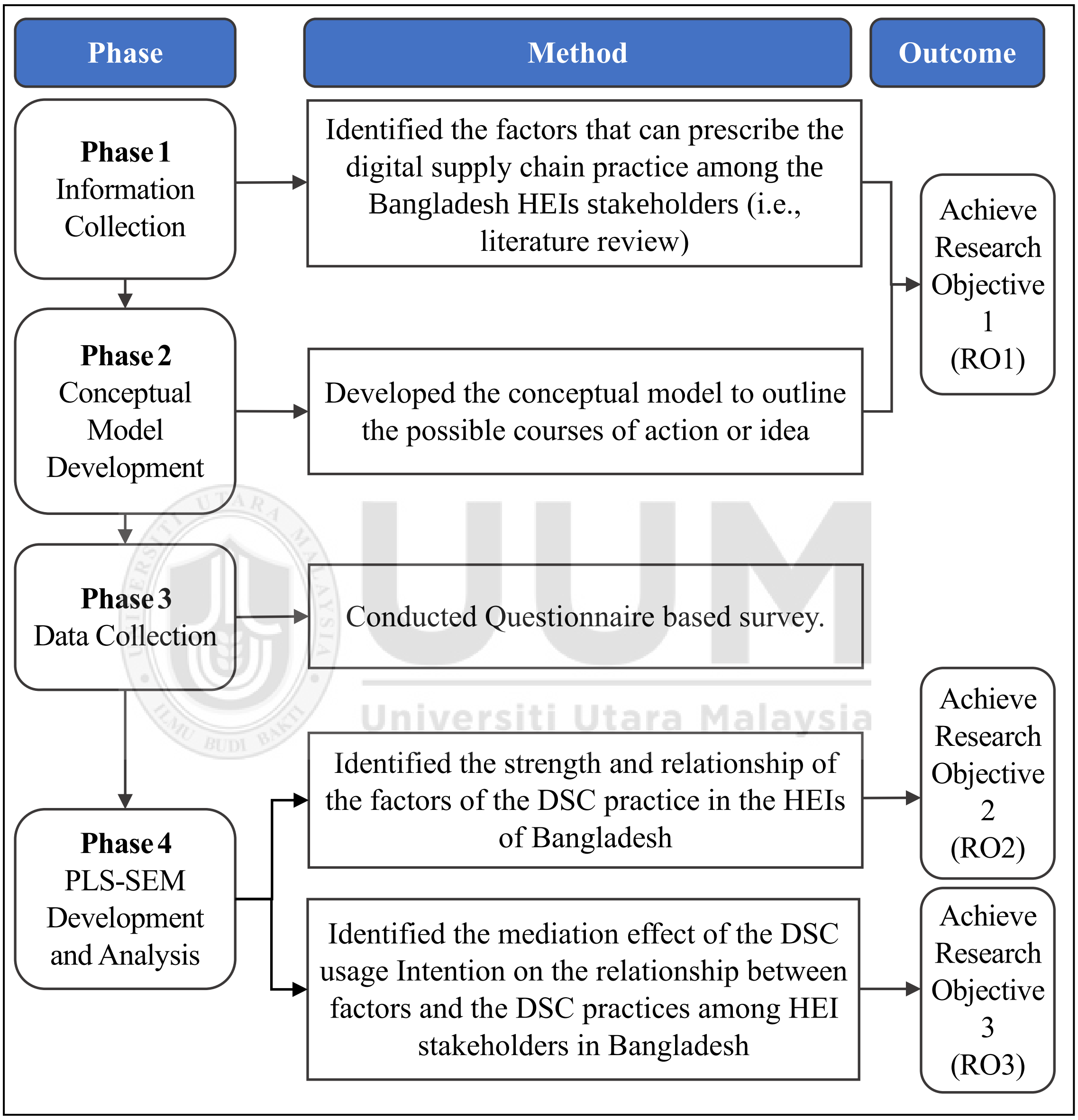

Figure 3.1. Flow of Research Process

The outcome received from each phase, adopted methodologies, and conducted analysis as well as the tools required to execute the research tasks in the respective phases are all explained in detail from Section 3.3 until Section 3.7. The flow of the overall research process is summarized in Figure 3.1.

3.3 Phase 1 - Information Collection

The aim of Phase 1 is to achieve first research objective (RO1), i.e., it involves the process of identifying the factors that related to concept of stakehodler's intention to use and adopt DSC practice in HEIs in LDCs. In this phase, the prime activity is to review relevant literature and select crucial findings from articles those are relevant and other similar related literature pertaining to the DSC concept, application of Supply Chain Management in Higher Educational Institutions, Digital Supply Chain Practices in Higher Education Institutions, overview and digitization condition of least developed countries and on their Higher Education Institutions. A summary of literature has been presented after every segment of Chapter 2. Focus of this phase is to fill the gap as found in the studies conducted previously and eventually the outcome of this phase is a prime contribution and novelty of this research where a conceptual framework of DSC Practice model for HEIs in Bangladesh is constructed, which has been explained with all the details in Chapter 2, Section 2.7. The outcome from this phase is used in Phase 2.

3.4 Phase 2 – Conceptual Model Development

In relation with achieving the first research objective (RO1), the aim of Phase 2 is to develop the conceptual model of DSC usage intention and adoption by the stakeholder of HEIs in Bangladesh is built. Based on the conceptual framework built in Phase 1, a set of hypotheses are constructed for further analysis, based on the paths and relationships among the factors as illustrated in the framework. The illustration of relationships and relevant hypotheses which were described in section 2.9 in detail are depicted in Figure 3.2.

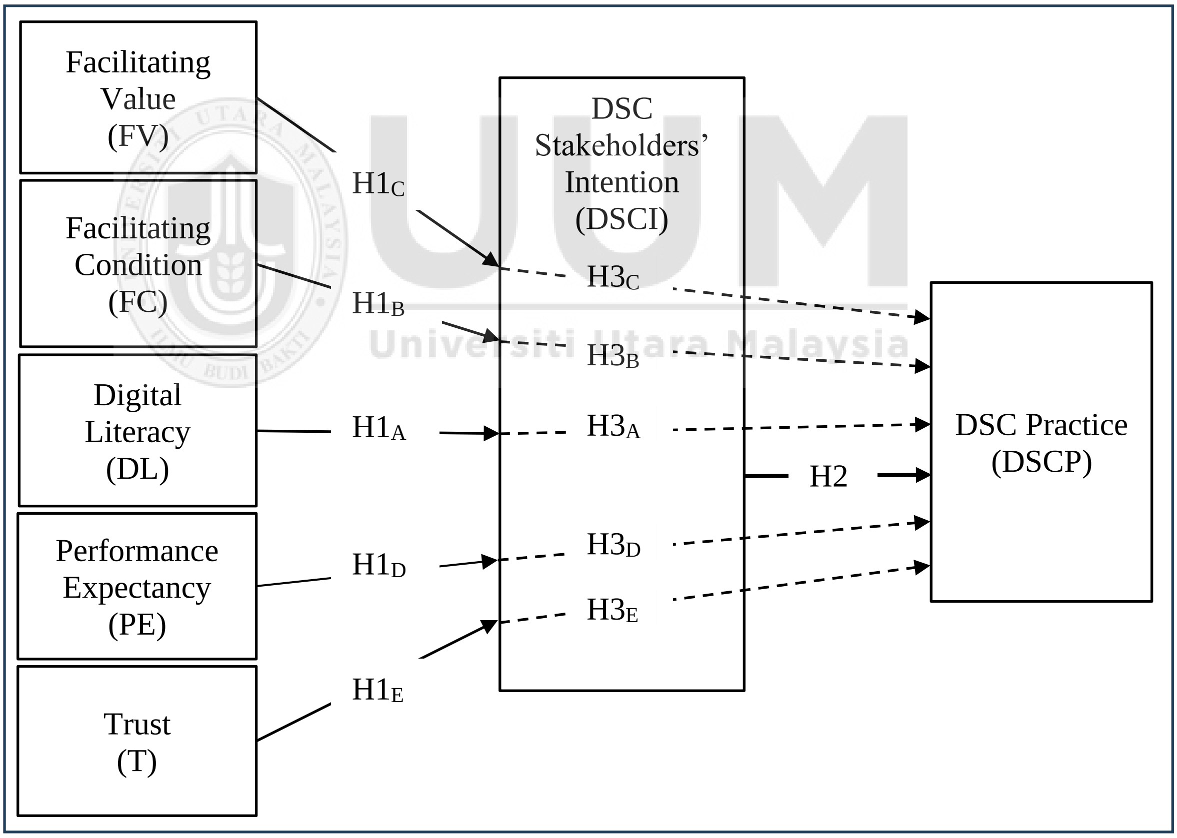

Figure 3.2. Research Conceptual Model of this Study

The hypotheses in the conceptual framework model constructed have been analyzed by using the Partial-Least Square Structural Equation Modeling (PLS-SEM) technique where the descriptions of data collected to test the model will be explained in Section 3.5 and the PLS-SEM in Section 3.6.

3.5 Phase 3 – Data collection

In this Phase 3, four main activities involved in the process of collecting the data. The detail description of all related activities conducted in this phase are all explained from Section 3.5.1 until Section 3.5.4.

3.5.1 Develop Questionnaire

Initially, items constructed in the first version of the questionnaire were designed relating to the research questions discussed in Chapter 1 and the conceptual model presented in Phase 2. A seven-digit numerical scale was applied to collect the responses of the respondents, ranging from 'strongly agree' to 'strongly disagree'. It was ensured that the questions are precise and direct. The questionnaire covered all constructs of the conceptual model. A total of 44 questionnaire items were designed and distributed over three sections. The first section collected respondents' demographic information, the second section collected respondents' opinion regarding the influence of factors of DSC usage intention (i.e., facilitating value, facilitating condition, digital literacy, trust, performance expectancy), and the third section collected respondents' opinion about DSC usage intention influencing their adoption of Digital Supply Chain practice. There was a short explanation at the beginning of the questionnaire, which easily stated the objective of the questionnaire to the respondents and an approximate timeframe was also informed to the respondents required to answer all questions. Moreover, a brief definition of each construct was also provided for respondents to clearly understand the impact of the attribute while making their choices.

After the design was ready, the questionnaire was tested for its validity and reliability using content validity test and pilot test respectively.

3.5.2 Validate the Content of the Questionnaire

Experts' judgement was applied to determine the validity of the questions relating to the objective of the research. Opinions of three experts in the fields of Higher Education Institute and Digital Supply Chain management were collected on the items of the questionnaire and their relevancy with the constructs, and eventually with the goal of the research.

Table 3.1

List of experts for content validity

Sl	Name	Position	Expertise Area
1	Prof. Dr. Ravindran Ramasamy	Graduate School of Business, University Tun Abdul Razak, Malaysia	PLS-SEM
2	Dr. Sudeshna Lahiri	Associate Professor. Department of Education, University of Calcutta	Higher Education

Table 3.1 Continued

Sl	Name	Position	Expertise Area
3	Dr. Ferdoush Saleheen	Chief Supply Chain Officer, Akij Food and Beverage Limited (AFBL) Adjunct Faculty, Brac University, Bangladesh	Digital Supply Chain and Supply Chain Education

Based on experts' opinion, the questionnaire was later revised, and some of the items were rephrased, relocated, and also removed, with aim of increasing their applicability towards the objective and relevancy to the constructs. Table 3.2 illustrates the summary of the revision. Combining sections 2 and 3 of the questionnaires, 44 items were eventually reduced to 34 items.

Table 3.2

List of Questionnaire Items and their status based on expert opinion

No of items	Variables and Items	Expert Opinion
Facilitating Value (FV)		
5	Digital tools, networking and ICT infrastructure in my university are reasonably priced. (FV1)	Maintain
	Digital tools, networking and ICT infrastructure in my university are good value for the money.	Remove

Table 3.2 Continued

No of items	Variables and Items	Expert Opinion
Facilitating Value (FV)		
	At the current price, digital tools, networking and ICT infrastructure in my university provides excellent value. (FV2)	Maintain
	Digital Supply Chain is capable to provide a better facility with a minimum cost incurring to the users in my university. (FV3)	Maintain
	The value of Digital Supply Chain in my University worth its price. (FV4)	Maintain
Facilitating Condition (FC)		
5	I have the necessary resources to use digital platform in my university. (FC1)	Maintain
	I know it is necessary to use digital platform in my university. (FC2)	Maintain
	Digital tools, networking and ICT infrastructure in my university are compatible with other personal technologies I use. (FC3)	Maintain
	I can get help from others when I have difficulties using digital tools, networking, and ICT infrastructure in my university. (FC4)	Maintain

Table 3.2 continued

No of items	Variables and Items	Expert Opinion
Facilitating Condition (FC)		
	My university always updates or changes its digital tools, networking, and ICT infrastructure with the latest version. (FC5)	Maintain
Digital Literacy (DL)		
6	I know how to solve my own ICT related technical problem. (DL1)	Maintain
	I know about a lot of different digital technologies	Remove
	I can learn new digital technologies easily. (DL2)	Maintain
	I have the technical skill I need to use digital tools, networking and ICT infrastructure in my university for working (e.g.: online teaching-learning) that demonstrate my understanding of what I have learnt. (DL3)	Maintain
	I am familiar with issues related to web-based activities (e.g.: plagiarism, cyber safety). (DL4)	Maintain
	I frequently obtain help with tasks from my friends over the Internet (e.g., through Facebook, Skype, Blogs). (DL5)	Maintain
Hedonic Motivation		Remove
5	Using digital tools, networking and ICT infrastructure at my University is informative.	Relocate to Performance Expectancy

Table 3.2 continued

No of items	Variables and Items	Expert Opinion
Hedonic Motivation		Remove
	Using digital tools, networking and ICT infrastructure in my University is educational.	Remove
	Using digital tools, networking and ICT infrastructure in my University is entertaining.	Remove
	I feel proud to use digital tools, networking and ICT infrastructure in my University	Remove
	I feel comfortable to use digital tools, networking and ICT infrastructure in my University	Remove
Trust (T)		
5	I trust the implementation of Digital Supply Chain in my University. (T1)	Maintain
	I feel assured that legal and technological structures are implemented adequately in my University to protect me from problems in Digital Supply Chain practices. (T2)	Maintain
	I have no doubt on the truthfulness of Digital Supply Chain in my University. (T3)	Rephrase
	Even if not monitored, I would trust the implementation of Digital Supply Chain practice to do the job correctly in my University. (T4)	Maintain

Table 3.2 continued

No of items	Variables and Items	Expert Opinion
	The Digital Supply Chain can fulfill my required tasks relevant to University management. (T5)	Maintain
Performance Expectancy (PE)		
5	Digital Supply Chain increases the completion of the work tasks that are important to me. (PE1)	Maintain
	Digital Supply Chain helps me accomplish work tasks more quickly. (PE2)	Maintain
	Digital Supply Chain increases my work productivity. (PE3)	Maintain
	Digital Supply Chain information received from other parties to complete my work tasks is always fast. (PE4)	Merge with one item from Hedonic Motivation
	I find Digital Supply Chain useful to enhance my University's performance. (PE5)	Maintain
DSC Stakeholders Intention (DSCI)		
5	I believe the Digital Supply Chain needs proper user intention. (DSCI 1)	Maintain
	Academic supply chain performance needs proper technology attraction. (DSCI 2)	Rephrase

Table 3.2 continued

No of items	Variables and Items	Expert Opinion
DSC Stakeholders Intention (DSCI)		
	User manual for digital supply chain practice is needed in my University to increase the productivity of academic supply chain. (DSCI 3)	Maintain
	I will continue practicing the digital supply chain for my work purpose in the future. (DSCI 4)	Maintain
	Organization's stakeholders need proper adaptability on technology adoption. (DSCI 5)	Maintain
Digital Supply Chain Practice (DSCP)		
5	I find Digital Supply Chain useful in my job. (DSCP 1)	Maintain
	Digital Supply Chain enables me to accomplish my job tasks more quickly. (DSCP 2)	Maintain
	Digital Supply Chain increases my job productivity. (DSCP 3)	Maintain
	In my institution, Digital Supply Chain enables me to receive fast, accurate and informative instruction/ information about my job. (DSCP 4)	Maintain
	Digital Supply Chain increases my creativity skills in doing my job. (DSCP 5)	Maintain

Then, once the content validity test was completed, the reliability of this questionnaire was examined using the pilot test.

3.5.3 Conduct the Pilot Test

A total of randomly selected 50 stakeholders of HEIs in LDCs were asked to answer the questionnaires. Collected data were statistically tested and are tabulated in Table 3.3. The Cronbach's Alpha value of the constructs ranged from .824 to .940 among the items during pilot test, which provide the evidence that there are high internal consistency among all the items used in these cases (Taber, 2018).

Table 3.3

Reliability test value (Cronbach's Alpha) of pilot test and final

Variable Name	**Number of Items**	**Cronbach's Alpha**	
		Pilot Test (Population = 50)	Final (Population = 434)
Facilitating Value	4	0.73	0.81
Facilitating Condition	5	0.82	0.86
Digital Literacy	5	0.83	0.81
Trust	5	0.76	0.87
Performance Expectancy	5	0.93	0.93
DSC Stakeholders Intention	5	0.73	0.84
Digital Supply Chain Practice	5	0.91	0.96

Other than Cronbach's Alpha value examination, the average time of how long the respondents answered the questionnaires and comments from the respondents were also considered for the questionnaire quality improvement. No respondent commented inversely on the wording of the items in the questionnaire. This worked as a pre-test of the questionnaire. Researchers need to perform pre-testing to prevent questionnaire ambiguity and confusion. It is performed to analyze all aspects of a questionnaire, such as question material, wording, formatting, sequence, and question instruction (Malhotra et al., 2009). The experts suggested using a slider scale allows users to submit more granular responses (Kemper et al., 2020). The respondent can slide the slider from left to right to set the answer number. A Slider Scale will usually be used to capture a percentage or other number within a defined range. A slider ranging from “0” to “100” was used to collect response to each question implying ‘0’ stands for “strongly disagree” and ‘100’ stands for “strongly agree” respectively. The question format in each section is based on a combination of both - closed-ended and semi-ended questions.

Other than the measurement scale, all the questions in the questionnaire were assured to be clear, concise, and direct. Hence, the final version of the questionnaire has been validated and significantly reliable in terms of all constructs of the conceptual model built in Figure 3.3, explained in Section 3.4.

3.5.4 Determine the Respondents’ Population and Sampling

A study's population usually consists of all the elements as per the interest of the researcher (Bougie & Sekaran, 2019; Taherdoost, 2016) that may be community, social action, individual or entity. Nevertheless, the truth is, it is completely impossible for a researcher to investigate the entire target population of interest. It is not feasible, in whichever means the researcher wants to perform the study, due to time, expense, and resource limitations (Bougie & Sekaran, 2019). Hence, defining the target population and sample accurately is important (Taherdoost, 2016; Marczyk et al., 2005).

Sampling is a method of gathering sample data (Bougie & Sekaran, 2019; Taherdoost, 2016). Population variations are clearly expressed in a good sample, which is capable of converge to a conclusion from a smaller sample representing the larger population (Hair et al., 2017). Hence, selection of appropriate samples from the population is highly essential as the they successfully exhibit the characteristics of the actual population. Roscoe et al. (1975) said a sample greater than 30 and less than 500 were appropriate for analysis. For the PLS-SEM analysis, Hair et al. (2017) claimed that the minimum sample size should be ten times the average distance to structural model construction. On the other hand, suggestion of Krejcie and Morgan (1970) is to consider a sample size of minimum 384 elements in case of a population size which is higher than 1,000,000. There is another sampling technique suggested by the Cochran formulas to determine the sample size (Cochran et al., 1954). Cochran mentioned two basic formulas to estimate the sample size. The first formula for unknown large number of population (generally more than 10,000) and the second one is for known number of populations. The formula for unknown population is

$$n_0 = \frac{Z^2pq}{e^2} \tag{3.1}$$

where,

n_0 is the sample size (unknown populations),

Z is the Z-value for confidence level,

p is the estimated proportion of an attribute that is present in the population,

q is $(1 - p)$, and e the percentage maximum error required or margin of error.

The second formula for the known population is:

$$n = \frac{n_0}{1+\frac{(n_0-1)}{N}} \tag{3.2}$$

here,

n_0 is the sample size (unknown populations) and

N is the population size.

In this study the simple random sampling technique is used to identify the respondents who are suitable to answer the questionnaire. The respondents are the stakeholders of HEIs in Bangladesh as idenfiied by the previous researchers in their studies of supply chain management in Academia, namely students, teachers, and adminitrative officials (i.e., Hye et al., 2014, Habib, 2014, Pathik et al., 2012b, Pathik et al., 2012c). As per the latest data of the University Grants Commission (UGC) of Bangladesh, the total number of students, faculties, and officials in 142 universities are presented in the Table 3.4 (University Grants Commission of Bangladesh, 2020)

Table 3.4

Population Size – total stakeholders of universities in Bangladesh

Category	**Total**
Number of Students	1,230,198
Number of Faculty Members	30,703
Number of Officials	47,668
Total Stakeholders	1,308,569

Based on the data tabulated in Table 3.4, considering Z-value is 1.96 at confidence level 95%, p is 0.5 as the variability in the proportion is unknown, the margin of error 0.05; the sample size is:

$$n_0 = \frac{(1.96)^2(0.5)(1-0.5)}{(0.05)^2} = 384.16 \approx 385.$$

Finally, the accepted sample size for the known population of 13,08,569 is

$$n = \frac{385}{1+\frac{(385-1)}{1308569}} = 384.05 \approx 385.$$

Hence, a total of 434 samples were collected which satisfies all previously stated sampling guidelines.

Due to COVID-19 pandemic, the questionnaire was distributed over Survey monkey online platform to the respondents. Hence, the data collection was reliable, fast and cost-effective. Besides that, it also ensured no missing data and normality of the data along with decreasing outliers.

3.6 Phase 4 – PLS-SEM Model Development

Phase 4 of the research process covered the activities of validating the data against the items of questions constructed for each dimension, verifying the dimension grouped in questionnaires and analyzing the inter-relations between the dimensions. The explanation is presented from Section 3.6.1 until Section 3.6.3.

3.6.1 Validate the Content of the Questionnaire with sample data

Before the PLS-SEM analysis can be conducted, the construct used in the questionnaire needs to be validated again. The questionnaire items were checked whether they are answered in the same manner as they are thought to be for the measurement of a construct (Costello & Osborne, 2005). As a validation process of the questionnaire content, the Kaiser-Meyer-Olkin (KMO) method was used to examine the items of questions. KMO values between 0.8 and 1 indicated sample sufficiency (Kaiser, 1974). In detail, the values of KMO that are close to 1 indicates that the sum of partial correlations is not large relative to the sum of correlations and the value KMO which is more than 0.9 is accepted as marvelous, 0.8 is accepted as meritorious, 0.7 is accepted middling, 0.6 is accepted as mediocre, 0.5 is assessed as miserable and less than 0.5 is unaccepted. While Hair et al. (2017) suggested that the value of more than 0.5 will be accepted where 0.5 until 0.7 is assessed as mediocre, and value between 0.7 and 0.8 is accepted as good. The other suggestion said that if KMO is lower than 0.6 value, the result suggests that sampling is not sufficient, and actions should be taken to remedy (Shrestha, 2021).

The Bartlett's test for sphericity was also examined to test whether the correlation matrix of the constructs is an identifying matrix. If the significant value is less than 0.05, it indicates that a factor analysis is worthwhile for the data set (Shrestha, 2021).

3.6.2 Verify the Dimensions of the Questionnaire

After the content of the questionnaire item has been validated, to identify the items that explain the constructs best, another verification test is required. The verification test was deployed using the Exploratory Factor Analysis (EFA), whereby it is normally used to minimize the quantity of questionnaire items. The EFA was conducted in SPSS in this particular research, where the items of questions are examined with the estimations of the factor extraction and rotation. The extraction of factor involves choosing the model type as well as the number of finally extracted factors. While factor rotation is conducted after the process of the factor extraction been completed, whereby it is important to improve the interpretability of the model. Three steps were carried out in EFA to ensure the quality of the constructs as below, and the results of these tests will be discussed in Chapter 4.

i. Scree Plot and Eigenvalues

To find out the number of factors or the principal components that will be considered for the model, scree plot was used. The eigenvalue of all the factors were plotted in the scree plot, which represents the amount of variance that can be explained by them. The factors with eigenvalues greater than zero are to be retained as the principal components in contrast to values closer to zero which implies multicollinearity (Shrestha, 2021).

ii. Communality

Afterwards, to solve the problem of commonalities, variance proportion of each item within each construct were examined. As per Yong and Pearce (2013), the estimated proportion of variable variance which is free of error variance can be used for the communality estimation. If the value is closer to 1, it suggests that the extracted factor explains the variance more. The Factor analysis considers variance in its method which was adopted in this research where the variance produces communalities.

iii. Factor Loading (Rotation Component Matrix)

Watkins (2018) illustrated that in case of Factor analysis, extraction is used to get rid of common variance as much as possible. An item with variance value less than 0.3 needs to be deleted from the questionnaire and a better item should be considered instead. Items are grouped based on the range in loading factors identified from obtained results in this analysis. Moreover, Varimax factor rotation process was also applied during the Factor Analysis for identifying the factor dimension. According to Truong and McColl (2011), for better results, factor loading should be greater than 0.5. In addition, Shkeer and Awang (2019) separated the factor loading values as higher than 0.5 for newly developed question or items and higher than 0.6 for established questions or items.

3.6.3 Analyze the Inter-relations between the Dimensions

The inter-relations between the dimensions were examined using the Partial Least Squares Structural Equation Modeling (PLS-SEM). Sarstedt et al. (2017) stated that PLS-SEM is a widely used method in estimating (complex) path models with latent variables. According to Hanafiah (2020), PLS-SEM is a method that uses logical models to represent the formative and reflective measurements model. This method combines sets or blocks of pointer linearly to form a composite, which can examine the existence of conceptual variables and assess how well these conceptual variables are accepted. PLS-SEM is a statistical method that examines the relationships between latent variables and their indicators. PLS-SEM is particularly useful when the sample size is small, few theories are available to guide the research, and when predictive accuracy is a priority. In contrast, reflective measurement scales are used to measure latent variables where the indicators are interchangeable and highly correlated with each other. PLS-SEM can be a good alternative to other structural equation modeling approaches when accurate model specification is challenging to achieve. (Jhora et al., 2020).

This method is well-suited to be used in this research because PLS-SEM offers good estimates for the general model that has validity for each content presented in providing a new guideline for higher education institute stakeholders, particularly in least developed countries while adopting digital supply chain practices. In this research, the factors identified reflect the intention and attitude of these stakeholders which conforms to the digital supply chair practices. Thus, the PLS-SEM qualifies for accuracy in the prediction of the model developed in this research. For a better understanding, the general model of PLS-SEM in this research is illustrated in Figure 3.3.

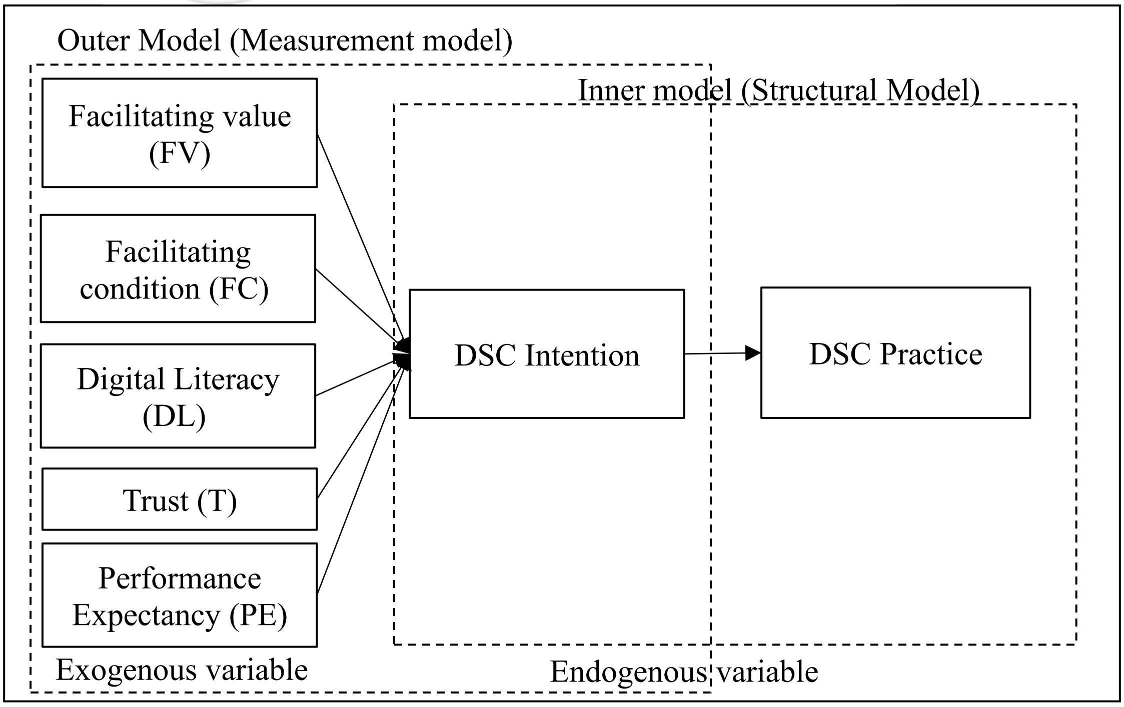

Figure 3.3. General model PLS-SEM

In Figure 3.3, there are two important sub-models, namely the inner model and outer model. For the Inner model, the model determines the relationship between the observable exogenous variables and endogenous latent variables. Meanwhile, the outer model determines the relationship between latent variables and the perceived indicators. Exogenous variables are defined as where it has an outward-pointing path and no direction leading to these variables, whereas the endogenous variable has at least one path leading to it. The summary of the variables is tabulated in Table 3.5.

Table 3.5

Variables of PLS-SEM structure for this research

Type of Variables	**Variables**
Exogenous / Independent	Facilitating Value (FV)
	Facilitating condition (FC)
	Digital literacy (DL)
	Trust (T)
	Performance Expectancy (PE)
Endogenous / Dependent	DSC usage Intention
	DSC Practice

To run the analysis, this research used the SmartPLS software as it is widely used in research related to path modeling analysis. Items to measure each variable for exogenous variables in this research are suggested by experts and tabulated in Table 3.2. Before the analysis of the PLS-SEM can be conducted, all the data were exported to SmartPLS software. Then, in this software, the inner and outer models were built.

The output from the SmartPLS presented path modeling estimations based on the conceptual model of this research. The results are presented in two models – one is the measurement model (outer) and the other is the structural model (inner). In the inner model, the numbers on the arrow from the latent exogenous variables (DL, FV, FC, T, PE) to their observable constructs represent their loading on the latent variable. On the other hand, in the outer model, the numbers on the arrows represent co-efficient strength among the endogenous latent variables. Other than these, the stability of the theoretical framework structure has also been tested. The evaluation criteria are explained in the upcoming sections.

a. Evaluation of Measurement (Outer) Model

i. Reliability

To evaluate the standardized outer loadings of the observed variables, the reliability of each of its indicator's variance is observed as it implies that the variance is explained by the latent design. It is accepted when the observed variables have more than 0.7 value of outer loading. The outer loading with less than 0.4 value is discarded. In case of exploratory research, the value of 0.4 or higher is considered as acceptable (Hair et al., 2011; Hair Jr et al., 2014; Wong, 2013).

Composite Reliability value is usually used because of its better assessment capability of internal consistency (Jin & Wang, 2019; Hair Jr et al., 2017). Generally, the acceptable value of composite reliability is either 0.7 or higher. But, in case of exploratory research, composite reliability value of 0.6 or higher is also considered as acceptable (Hair Jr et al., 2017). The formula to calculate the value of Composite Reliability (CR) is:

$$CR = \frac{(\sum_{i=1}^{M} l_i)^2}{(\sum_{i=1}^{M} l_i)^2 + \sum_{i=1}^{M} var(e_i)} \quad (3.3)$$

where,

with *M* number of indicators, l_i represents the standardized outer loading of the indicator variable *i* of a specific construct

i is the number of items

e_i is the error measurement of the indicator variable *i*

$var(e_i)$ represents the error measurement variance equivalent to $1 - l_i^2$

ii. Convergent Validity

The level of positive associations between variables within the same model must be high for a model to be considered valid (Jin & Wang, 2019; Hair et al., 2017). Average Variance Extracted (AVE) number is suitable to test the convergent validity of measurement model. It should be 0.5 or higher (Jin & Wang, 2019; Hair et al., 2017; Henseler, 2017) and the formula to calculate the AVE is:

$$AVE = \left(\frac{\sum_{i=1}^{M} l_i^2}{M}\right) \quad (3.4)$$

where,

with *M* number of indicators, l_i represents the standardized outer loading of the indicator variable *i* of a specific construct

iii. Discriminant Validity

Fornell and Larcker (1981) recommend that the "square root" of each latent variable's Average Variance Extracted (AVE) value should be more than the correlations among all the latent variables. That means all construct pairs satisfied the criterion (Ab Hamid et al., 2017). The square root of each construct's AVE must be higher than its maximum correlation measured with any other construct. The idea behind of Fornell-Larcker method of discriminant validity is that a construct shares higher variance with its own associated indicators than it does with other constructs that are there, i.e.,

$$\sqrt{AVE(y_i)} \geq corr(y_i, y_j) \tag{3.5}$$

However, some researchers find heterotrait-monotrait ratio (HTMT) is more appropriate in identifying the discriminant validity when the value of HTMT is lower than 0.85 (threshold value). HTMT is calculated from the mean of all correlations of indicators across constructs measuring different constructs relative to the mean of the average correlations of indicators measuring the same construct (Hair Jr et al., 2017; Goodhue et al., 2012; Henseler et al., 2009).

b. Evaluation of Structural (Inner) Model

Once the outer measurement model was confirmed valid and reliable, the researcher needs to evaluate the inner structural model. In this part of the analysis, the model's predictive relevancy and the relationships between the constructs are observed. The statistical test-based evaluation criteria of this section are described below:

i. Evaluation of Structural Model Collinearity

Variance inflated factor (VIF) can be measured to investigate the presence of multicollinearity among the exogenous latent variables. VIF greater than five has been shown by Hair and colleagues (Hair et al., 2017) to imply the presence of multicollinearity. The structural model VIF values for the exogenous component must be less than the cut-off values for the components (5) (Hair et al., 2017).

ii. Coefficient of Determination (R^2)

For the structural model, the overall effect size and variance explained in the endogenous construct is measured by the coefficient of determination. Hence, it measures the model's predictive accuracy (Hussain et al., 2018). Hair et al (2013) suggested that the value of R^2 when more than 0.75 is considered as substantial, 0.50 is considered as moderate, 0.26 is weak. The adjusted coefficient of determination is defined as:

$$R^2_{adj} = 1 - (1 - R^2).\frac{n-1}{n-k-1} \tag{3.6}$$

here,

n is the sample size

k is the total number of exogenous latent variable

R^2 is the squared correlation of actual and predicted values

iii. Path coefficient (β value)

Through the measurement of β value, the significance of the hypothesis was eventually tested. The higher the beta coefficient (β) value, the stronger the effect of an exogenous latent construct is observed on the endogenous latent construct.

iv. T-statistic value

However, the significance level of measured β value needs to be verified through the T-statistics test. The bootstrapping test and check the t-value > 1.96 (for 2-tailed) which is equivalent to $p < 0.05$ (Hair et al., 2021).

v. Level of Effect Size (f^2)

Purwanto and Sudargini (2021) and Hair et al. (2017) suggested the values of f^2 as 0.35, 0.15, and 0.02 should be taken as large, medium, and small effects among the constructs respectively. It is measured in addition to Coefficient of Determination (R^2) values, where the effect of the exogenous construct on the endogenous construct is assessed if the exogenous construct is removed. The size of the effect is calculated as

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} \tag{3.7}$$

vi. Predictive relevance of the model (Q^2)

Q^2 statistics are required to assess the quality of the PLS path model. The blindfolding process is used for this calculation. Q^2 the criterion in this part can be recommended to predict the endogenous latent construct using the conceptual model (Hair et al. 2021). Q^2 shows how well the empirically collected data can be reconstructed using PLS parameters and the model. Q^2 must be greater than 0.5 for endogenous latent constructs to be relevant and adequate and the formula to calculate Q^2 is:

$$Q^2 = 1 - \frac{\sum_D E_D}{\sum_D O_D} \tag{3.8}$$

where,

E = Sum of squares of prediction error

O = Sum of squares error using the mean for prediction

D = Omission distance

(Akter et al. 2011)

vii. Goodness-of-Fit (GOF)

To validate a model that describes empirical data, an index for a complete and appropriate model should be used and it is known as Goodness-of-Fit (GOF). The measured value of GOF falls between 0 and 1, and the value more than 0.36 is considered to large indicator of the global validation of the PLS-SEM path model (Hussain et al., 2018). Other than that, the value 0.25 is considered as a medium, and 0.10 is considered as small. The GoF is calculated by the formula of the square roots of the average mean of R^2 multiple by AVE and the model GoF is shown below.

$$\text{GoF} = \sqrt{Average\ R^2 * Average\ AVE} \tag{3.9}$$

where

R^2 = Coefficient of determination

AVE = Average Variance Extracted

viii. The Standardized Root Mean Square Residual (SRMR)

Difference between the model implied correlation matrix and the observed correlation were measured with SRMR. Hair et al. (2017) said the value SRMR that is less than 0.08 are considered a good fit for the model development using PLS-SEM.

ix. Normed Fit Index (NFI)

Normed Fit Index (NFI) assesses the discrepancy between the chi-squared value of the hypothesized model and the chi-squared value of the null model. NFI results in values between 0 and 1. Dash and Paul (2021), and Hair et al. (2021) stated that the closer the NFI value to 1, the better the model will be fit. NFI value higher than 0.9 usually represent an ideal acceptable fit.

x. Root Mean Square residual covariance (RMS $_{theta}$):

Introduced by Dash and Paul (2021) and Hair et al. (2021), based on the discrepancy between correlations of implied model and variance observed, the Root Mean Square residual covariance (RMS $_{theta}$) value is also a model fit measure. A conservative threshold value of RMS $_{theta}$ is 0.12 indicating a well-fit model (Hair et al., 2017).

xi. Correlation Coefficient of Latent Variables

The expected correlations among the observed variables with different latent variables where the values of correlation coefficient lie between 0 and 1.

The findings of the PLS-SEM analysis will be presented in Chapter 4.

3.7 Summary of Chapter

This chapter describes the methodologies adopted in this research, which is focused on the prime objective to develop a model of factors that influences digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh. It comprises of findings and analysis of the key factors that influence the HEI stakeholders' intention of adopting the digital supply chain practices towards improving its functionalities and services in the higher education institutes. The detail of how the research process is carried out phase by phase in terms of information collection, conceptual model development, data collection, and PLS-SEM model development and analysis are presented in this chapter, along with the methods of assessment and validation of the findings.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, observed findings and results of this research in alignment with the prime objective to develop a model of digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh are discussed in an organized manner, distributed over various sections. Starting with respondents' demographic analysis in section 4.2, the results of the Exploratory Factor Analysis are discussed in section 4.3 that confirm the factors that prescribe the practice of Digital Supply Chain (DSC) among the Bangladesh HEIs stakeholders. In Section 4.4, the Partial Least Square – Structural Equation Modeling (PLS-SEM) findings are presented in respect of the measurement model and the structural model. The chapter is finally concluded with a summary in section 4.5.

4.2 Respondents Demographic

Table 4.1 present a total of 434 stakeholders were studied in this study, where 82.49% were university students (358 respondents), 11.98% university teachers (52 respondents), and 5.53% university administrators (24 respondents) of Bangladesh HEIs. Female respondents showed a total of 26.9% (117 respondents) of the sample while male respondents a total of 73.04% (317 respondents). The highest number of respondents who answered this questionnaire were aged between 19 to 25 years, which showed a total of 68.43% (297 respondents), while followed by respondents aged between 26 to 35 is 17.51% (76 respondents), aged between 36 to 45 year is 8.06% (35 respondents), and the lowest is the aged range between 46 and above which is 5.99% (26 respondents).

In terms of highest academic level, approximately 68.66% (298 respondents) of the respondents have Bachelors' degree, 23.96% (104 respondents) of the respondents have Masters, 5.99% (26 respondents) of the respondents have PhD, 1.15% (5 respondents) of the respondents have other study, and the lowest one is respondents who have diploma which is 0.23% (1 respondent). For marital status, the highest respondent is still single which is 81.34% (353 respondents) and the rest are already married which is 18.66% (81 respondents).

Besides, in terms of family income by the respondents, the lowest family income is below $500 with highest percentage of 33.64% (146 respondents), followed by family income between $501 and $1000 which is 29.26% (127 respondents), family income between $1001 and $1500 which is 19.12% (83 respondents), family income between $1501 and $2000 which is 8.76% (38 respondents), and the highest family income is $2000, and above which is 9.22% (40 respondents).

A total of 434 respondents from Bangladesh HEIs in this study show that most of them comes from urban areas of 77.65% (337 respondents), followed by suburban areas with 12.44% (54 respondents), and the lowest is from rural areas of only 9.91% (43 respondents).

Table 4.1

Respondents Demographic

Demographic Data (Total Respondent = 434)	**Count**	**Percentage**
Gender		
Male	317	73.04%
Female	117	26.96%
Age		
19-25	297	68.43%
26-35	76	17.51%
36-45	35	8.06%
46 and above	26	5.99%
Education		
Diploma	1	0.23%
Bachelor	298	68.66%
Masters	104	23.96%
PhD	26	5.99%
Other Study	5	1.15%
Marital Status		
Single	353	81.34%
Married	81	18.66%
Occupation		
Student	358	82.49%
Teacher	52	11.98%
Administrator	24	5.53%
Income (in US Dollar)		
Below $500	146	33.64%
$501 - $1,000	127	29.26%
$1,001 – $1,500	83	19.12%
$1,501 - $2,000	38	8.76%
Above $2,000	40	9.22%

Table 4.1 continued

Demographic Data (Total Respondent = 434)	Count	Percentage
Location		
Urban	337	77.65%
Rural	43	9.91%
Suburban	54	12.44%

4.3 Assessment of Validation and Verification of Dimensions in Model Framework

This section of the research presents the data analysis conducted for validating the questionnaire items, correlations of the constructs and identify the number of factors (or constructs) that need to be used in this study.

The KMO and Bartlett's test was conducted, and the outcome result test is presented in Table 4.2. From this table, the values were higher than 0.6, which reflects that the questionnaire constructs of this research are all valid as stated with various references in section 3.6.2.

Table 4.2

Kaiser-Meyer-Olkin (KMO) Measurement

Variable Name	N of Items	KMO
Facilitating Value (FV)	4	0.791
Facilitating Condition (FC)	5	0.860
Digital Literacy (DL)	5	0.819
Trust (T)	5	0.829

Table 4.2 continued

Variable Name	N of Items	KMO
Performance Expectancy (PE)	5	0.899
DSC Stakeholders Intention (DSCI)	5	0.817
Digital Supply Chain Practice (DSCP)	5	0.910

The Bartlett's test for sphericity was also examined to test whether the correlation matrix of the constructs is found to be an identifying matrix. The results of KMO and Bartlett's test of sphericity is presented in Table 4.3. This test is used to ensure that all respondents' answers for each question item used are reliable or appropriate to this study. The measured result of KMO value is calculated as 0.966 and hence the value is marvelous and highly reliable (Kaiser, 1974). Besides that, Bartlett's test of sphericity shows that the variables are correlated enough where the correlation matrix diverges significantly from the identity matrix. As the significant value is less than 0.05, it indicates that a factor analysis is worthwhile for the data set (Shrestha, 2021).

Table 4.3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.954
Bartlett's Test of Sphericity	Approx. Chi-Square	11143.379
	df	561
	Sig.	.000

In addition, the number of factors that are necessary for this study were analyzed, which is illustrated in the scree plot (Figure 4.1). Figure 4.1 suggests that there are seven factors which signifies the dependent variable and independent variable in this study where this factor is determined when the eigenvalue value is more than one.

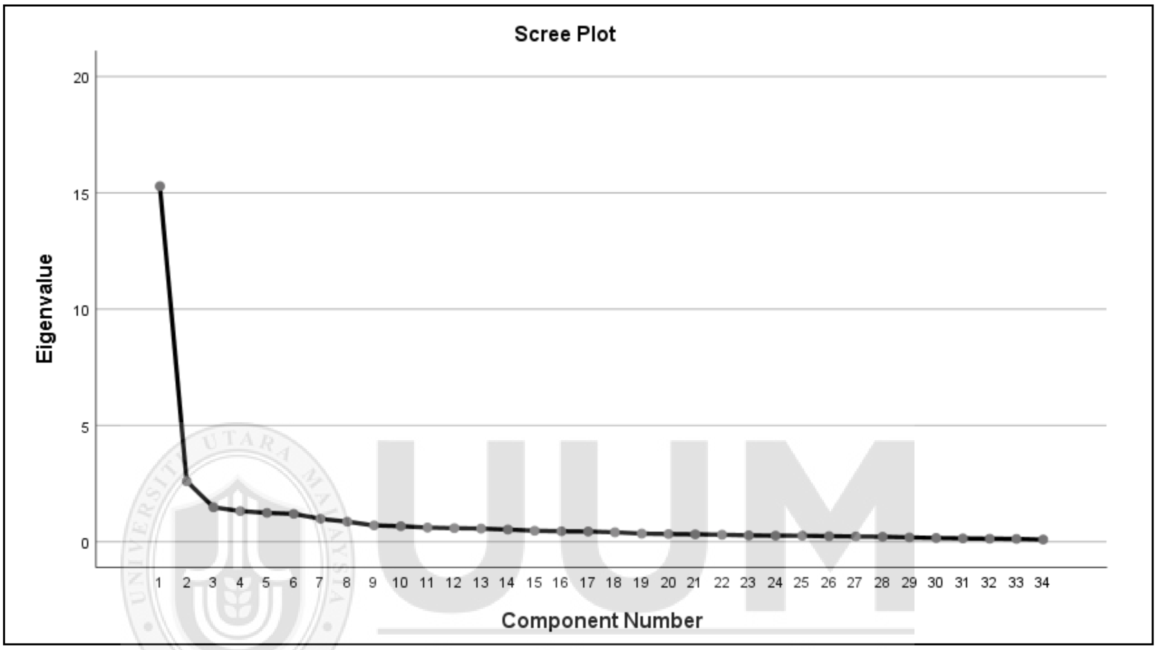

Figure 4.1. Scree Plot

To identify factor dimensions for this study, this study applied exploratory factor analysis (EFA) and Varimax rotation procedures. A total of seven factors have been extracted and rotated by the Varimax analysis. The results of the scree plot were supported by their eigenvalue output as illustrated in Table 4.4. This table explains that the seven constructs are explained with 73.17% of the variance. The proportion of the total variance explained by the retained factors is suggested to be at least 50% (Shrestha, 2021). Hence, using seven factors to represent the dependent and independent variables are reliable and viable in this study.

Table 4.4

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.282	44.948	44.948	15.282	44.948	44.948	5.793	17.038	17.038
2	2.600	7.648	52.596	2.600	7.648	52.596	5.155	15.160	32.199
3	1.483	4.361	56.956	1.483	4.361	56.956	3.439	10.116	42.315
4	1.318	3.877	60.833	1.318	3.877	60.833	3.074	9.041	51.356
5	1.240	3.648	64.481	1.240	3.648	64.481	2.921	8.592	59.948
6	1.198	3.523	68.005	1.198	3.523	68.005	2.203	6.479	66.427
7	1.087	2.902	70.907	1.087	2.902	70.907	1.523	4.480	70.907
8	.862	2.535	73.441						

Extraction Method: Principal Component Analysis.

Then, communalities were examined to avoid problems in each item. Through communalities, the relationship between items were known and explained. For example, the first component explains 14.3% of the total variance with eigenvalue 19.07 and the seventh component explaining 7.1% with 1.127 eigenvalue. During communalities was examined, if their communalities percentage is too low, it will be clear that the variables studied did not have much in common with the other variables. This means, the low extraction values need to be eliminated or discarded. Based on

Table 4.4, all items have communalities of above 0.40, therefore, they are related to the other items. This was supported by the research of Costello and Osborne (2005). Besides, Costello and Osborne (2005) explained that the value of communalities that are less than 0.4 needs to be eliminated and cut off from this study.

In this study, the researcher intended to identify factors that can represent stakeholders' usage intention and adoption of the DSC's general practices in the HEIs in least developed countries, where a total of 34 items were accounted for in the analysis. The numeric semantic scaled questionnaire was developed and distributed to institutions of higher learning in Bangladesh. A total of 434 respondents comprising of students, teachers, and administrators were surveyed.

In conclusion, the EFA results depict that all the items were retained along with the seven (7) constructs - Facilitating value (FV), Facilitating Condition (FC), Digital Literacy (DL), Trust (T), Performance expectancy (PE), Digital Supply Chain Usage Intention (DSCI), and Digital Supply Chain Practice (DSCP) were identified as tabulated in Table 3.2.

After all the constructs and their items are finalized through their validation assessment and verification of dimensions in Model Framework, structural equation modeling (SEM) with partial least squares (PLS) path modeling is applied to visually display relationship among the variables and the hypotheses that are examined in this research as illustrated in the next sections.

4.4 Assessment of PLS-SEM Findings

This section presents the outcome of measurements of using the second-generation multivariate analysis called Partial Least Square Structural Equation Modeling (PLS-SEM) (Hair et al., 2021). Section 4.4.1 describes the assessment of the measurement model, also referred to as the outer model of the constructs that display the relationships between the constructs and the indicator items (rectangles) that represent the constructs (circles or ovals). In Section 4.4.2, the assessment of the structural model is presented, also referred to as the inner model that displays the relationships (paths) between the constructs (circles or ovals). The assessment of the significance of the structural model relationship is analyzed in section 4.4.3.

In section 4.4.4, the assessment of the structural model with mediation is described. It is necessary to implement these requirements in a two-step procedure by conducting an external model evaluation and an internal model assessment (Becker et al., 2012). The measurement model is known as the outer model, and the structural model is the inner model (Wong, 2013). The measurement model is the first step in model assessment (Sarstedt et al., 2019). There are two types of measurement models: reflective and formative (Tehseen et al., 2017). The indicators were accurate representations of the findings of the study.

4.4.1 Assessment of Measurement (Outer) Model

It is necessary to assess the measurement model in terms of a number of different parameters. The reliability and validity of the reflected measurement model are tested using these characteristics (Cheah et al., 2018). That is, the reliability of the particular indicator or item, the dependability of the internal consistency, the validity of the discriminating element, and the reliability of the discriminatory element are all considered (Hair et al., 2017; Hair et al., 2014; Cousineau & Chartier, 2010). Figure 4.2 depicts the measurement model, and Table 4.5 summarizes the results of the measurement model. Description of the analysis is as follows.

i. Reliability

The reliability of each predictor item should be evaluated because it varies amongst researchers (Hair et al., 2021). The indicator's dependability is sometimes addressed to as "outer loading," it implies that, eventually the indicator's variance is explained by the latent design. The total load fluctuates between 0 and 1 based on the application. The basic standard rule is that loadings above 0.708 are recommended as they indicate that the construct explains more than 50 percent indicator’s variance (Hair et al., 2019). From Table 4.5, all the 34 predictor items in this study either have higher or close to the recommended value which means they successfully and reliably explain their constructs.

ii. Internal Consistency Reliability

Cronbach's alpha and composite reliability are analyzed as internal consistency tests (Henseler et al., 2009). It is desirable to have composite reliability value between 0.6 and 0.7 and considered as acceptable in exploratory research and value between 0.7 and 0.9 ranges from satisfactory to good (Hair et al., 2017). Composite reliability scores in this study were above 0.7, as presented in Table 4.5. Hence, the internal consistency of the items while explaining their respective constructs used in this study are reliable and acceptable.

iii. Convergent Validity

In order for a model to be considered valid, the level of positive associations between other variables within the same model must be high (Jin & Wang, 2019; Hair et al., 2017). The AVE values of latent variables as presented in table 4.5 were found to be higher than the cutoff value, 0.50 in this study, indicating that the latent variables were rendered convergent (Table 4.5). Thus, the measure of 7 constructs in this study, Facilitating value (FV), Facilitating Condition (FC), Digital Literacy (DL), Trust (T), Performance expectancy (PE), Digital Supply Chain usage Intention (DSCI), and Digital Supply Chain Practice (DSCP) have high levels of convergent validity, which eventually indicates that these constructs and their corresponding predictor items are highly reliable and valid to identify the impact of stakeholders intention to adopt digital supply chain practices in higher education institutes of Bangladesh.

Table 4.5

Psychometric Properties of the Constructs

Constructs	**Items**	**Loadings**	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Facilitating Value	FV1	0.74	0.81	0.87	0.63
	FV2	0.84			
	FV3	0.85			
	FV4	0.75			
Facilitating Condition	FC1	0.75	0.86	0.90	0.64
	FC2	0.78			
	FC3	0.83			
	FC4	0.84			
	FC5	0.81			

Table 4.5 continued

Constructs	**Items**	**Loadings**	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Digital Literacy	DL1	0.72	0.81	0.87	0.57
	DL2	0.84			
	DL3	0.84			
	DL4	0.78			
	DL5	0.58			
Trust	T1	0.90	0.87	0.91	0.66
	T2	0.89			
	T3	0.64			
	T4	0.76			
	T5	0.85			
Performance Expectancy	PE1	0.88	0.93	0.95	0.79
	PE2	0.90			
	PE3	0.94			
	PE4	0.86			
	PE5	0.87			
Digital Supply Chain Intention	DSI1	0.83	0.84	0.89	0.61
	DSI2	0.60			
	DSI3	0.82			
	DSI4	0.85			
	DSI5	0.79			
Digital Supply Chain Practice	DSP1	0.91	0.96	0.97	0.86
	DSP2	0.94			
	DSP3	0.94			
	DSP4	0.92			
	DSP5	0.92			

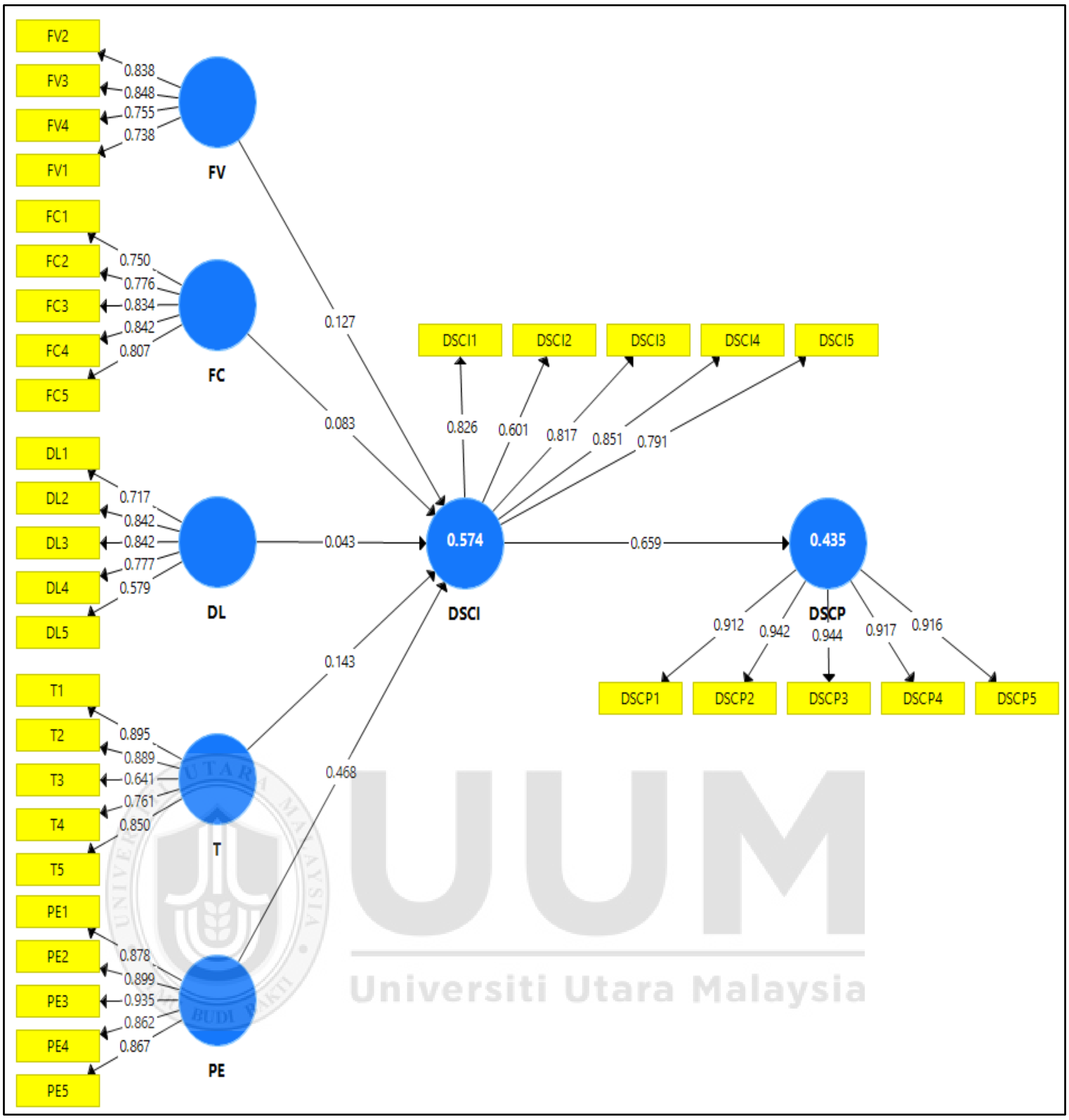

Figure 4.2. Measurement model

iv. Discriminant Validity

According to Fornell-Larcker (1981) the square root of the average variance extracted (AVE) compared with the correlation of latent constructs can be used to assess the discriminant validity. A latent construct can explain better the variance of its own indicators rather than the variance of other latent constructs. Hence, the square root of each construct's AVE must be higher than its correlation value with other latent constructs (Ab Hamid et al., 2017). But some researchers suggest that Fornell-Larcker criterion fails to function when the loadings are different in the attempt to determine discriminative validity (Hair et al., 2017). An evaluation of the correlation heterotrait-monotrait ratio (HTMT) is recommended by Henseler et al. (2009) as a potential cure. The trait is comprised of the intermediate and intermediate quotas of HTMT (Hair et al., 2017; Goodhue et al., 2012; Henseler et al., 2009; Chin, 2001). When the HTMT is more than 0.90, there is no differentiation between the two groups.

As tabulated in Table 4.7, the HTMT values of the constructs are lower than 0.9 which means the constructs are all distinctly discriminant from each other and measuring the factors specifically fulfilling the purpose they are adopted in this research. The latent construction ratios of Fornell-Larker were within the threshold in Table 4.6, indicating that the latent structure in this investigation was distinct from the other latent structures. Both Fornell-Larker and HTMT methods provided evidence that the 7 constructs of this study, Facilitating value (FV), Facilitating Condition (FC), Digital Literacy (DL), Trust (T), Performance expectancy (PE), Digital Supply Chain usage Intention (DSCI), and Digital Supply Chain Practice (DSCP) are distinct with acceptable value of discriminant validity.

Table 4.6

Fornell-Larker criterion of Discriminant Validity

	DL	**DSCI**	**DSCP**	**FC**	**FV**	**PE**	**T**
DL	0.758						
DSCI	0.507	0.782					
DSCP	0.375	0.659	0.926				
FC	0.554	0.555	0.473	0.802			

Table 4.6 Continued

	DL	DSCI	DSCP	FC	FV	PE	T
FV	0.505	0.548	0.461	0.552	0.796		
PE	0.578	0.727	0.699	0.606	0.560	0.889	
T	0.589	0.674	0.620	0.663	0.640	0.791	0.813

Table 4.7

HTMT Ratio of Discriminant Validity

	DL	DSCI	DSCP	FC	FV	PE	T
DL							
DSCI	0.596						
DSCP	0.421	0.723					
FC	0.656	0.631	0.518				
FV	0.614	0.652	0.524	0.664			
PE	0.659	0.802	0.739	0.669	0.642		
T	0.696	0.770	0.676	0.759	0.760	0.868	

The data analysis presented in section 4.4.1 determined the factors, Facilitating value (FV), Facilitating Condition (FC), Digital Literacy (DL), Trust (T), Performance expectancy (PE), and also their validity and reliability to represent the stakeholders intention to adopt Digital Supply Chain practices in higher education institutes in Bangladesh as a member of least developed countries (LDCs) which serves as the Research Objective 1 (RO1) of this study.

4.4.2 Assessment of Structural (Inner) Model

Researchers next concentrate on the structural model evaluation for PLS-SEM analysis following the evaluation of the measurement model (Hair et al., 2017; Hair et al., 2011). The internal model/structural model depicts the relationship between the latent buildings and the surrounding environment (Hair et al., 2012). Using the exogenous latent structures to explain the hypothesis testing, the structural model shows its route coefficients as well as how much variation there is, how big it is, and how important it is to predict (Ramayah et al., 2018; Hair et al., 2017; Hair et al., 2014; Hair et al., 2012; Hair et al., 2011). To test the structural model, researchers went through a series of stages, as depicted in Figure 4.3. The bootstrapping option with 500 samples was carried out with Complete Bootstrapping, Accelerated Bootstrapping, and Bias-Corrected at a 0.05 level of significance, and the results are presented in Table 4.8.

i. Assessment of Structural (Inner) Model Collinearity

It is necessary to determine whether there is presence of multicollinearity in exogenous latent buildings or not in order to conduct the first step of the structural model evaluation. The presence of multicollinearity can be investigated using a variance inflated factor (VIF), as a VIF greater than five has been shown by Hair and colleagues (2017) to imply the presence of multicollinearity. The VIF generated by the Smart PLS software system is both internal and external. The VIF interpretation for the internal model is shown in Table 4.8 for reference. As indicated in Table 4.8, the structural model VIF values for the exogenous component are lower than the accepted cut-off value, i.e., 5 (five). As per Hair et al. (2017), the acceptable value of VIF is between 0.2 to 5. The results of this study showed that multicollinearity among predictor items did not exist (Table 4.8), which was in accordance with the advice of Hair (2017). As evident in table 4.8, the VIF value of all of the exogenous variable, Facilitating value (FV), Facilitating Condition (FC), Digital Literacy (DL), Trust (T) Performance expectancy (PE) and Digital Supply Chain usage intention (DSCI) are well within the acceptable range.

Table 4.8

Variance Inflated Factor (VIF) of the exogenous variables

	DL	**DSCI**	**DSCP**	**FC**	**FV**	**PE**	**TR**
DL		1.749					
DSCI			1.000				
DSCP							
FC		2.014					
FV		1.830					
PE		2.866					
T		3.482					

ii. Assessment of Variance Explained (*R^2* or Coefficient of Determination)

The authors of Urbach and Ahlemann (2010) advocated reaching an absolute R^2 value for a model to have a minimum degree of explanatory power. Hair et al (2013) suggested that the value of R^2 when more than 0.75 is considered as substantial, 0.50 is considered as moderate, 0.26 is weak.

The R^2 values in table 4.9 demonstrate two endogenous constructs in this research (DSCP and DSCI). According to the study results, 57% of the total variance in DSCP adoption and 43% of the DSCI variance were explained. Five independent constructs

(DL, FC, FV, PE, and T) with a mediator (DSCI) predicted 34% of the variability in DSCP. For this reason, it can be said that the model of this study created appropriate R^2 values since the researcher's recommended threshold level has been met (Hair et al., 2021).

Table 4.9

Coefficient of Determination (R^2 values)

Variables	$\boldsymbol{R^2}$
DSCI	0.569
DSCP	0.434

iii. Assessment of the Significance of Structural Model Relationships (Path coefficient *β* value and T-statistic value)

During this stage, the relationship of the structural model with the latent buildings is calculated by PLS-SEM, that reflects the predicted relationship between the latent buildings (Hair et al., 2019, Ramayah et al., 2018; Hair Jr et al., 2017; Hair Jr et al., 2014). The use of *t*- and *p*-values specifies a specific association, without considering whether it is necessary or not. PLS-SEM employs an observational *t* and *p*-value boot-strapping technique to determine the sample size (Hair *et al.*, 2019; Hair Jr *et al.*, 2017; Hair Jr *et al.*, 2014). Statistically, *t*-values more than 1.645 are significant and *p*-values 0.05 or lower are accepted or supported (Ramayah *et al.*, 2018). To approximate the direction coefficients value, this study uses regular bootstrapping with a range of 500 bootstraps of 434 cases. As depicted in Figures 4.3, the conceptual model for this investigation includes latent external mechanisms, a mediator (DSCI), and a latent endogenous variable (DSCP).

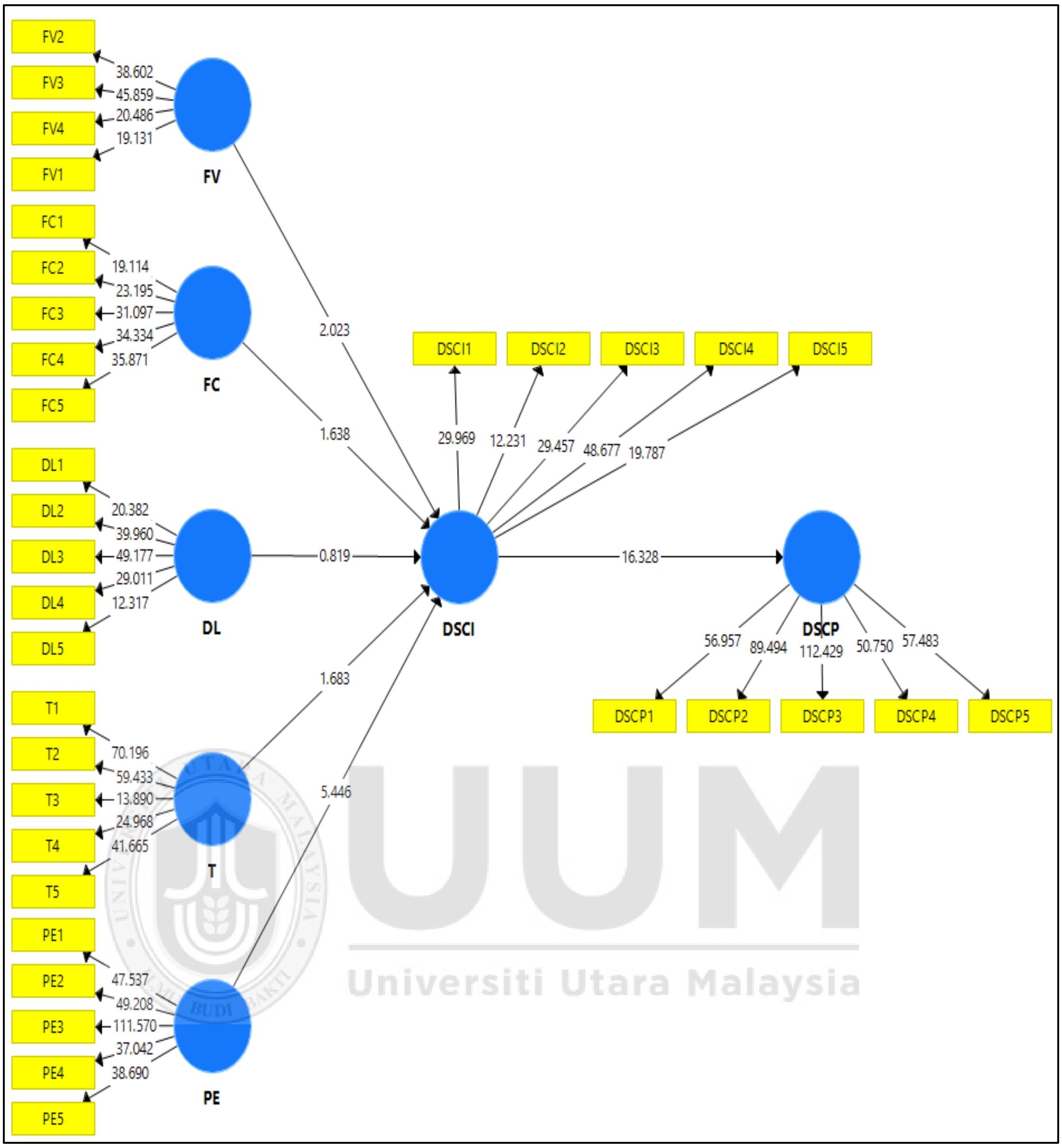

Figure 4.3. Structural Model

The structural model shows causal connections between buildings that determine the route values (Ramayah et al., 2018). The interactions observed in the structural model are tabulated in Table 4.11. Data relevant to hypotheses H1 and H2 of this study are tabulated in table 4.10. Hypothesis H1$_A$ showed that digital literacy directly predicts DSC intention since their relationship was significant (β = 0.043, t = 0.819, and p = 0.041).

Similarly, the relationship between facilitating condition and DSC intention was significant (β = 0.083, t = 1.638, and p = 0.012), and hypothesis $H1_B$ was supported. Likewise, hypothesis $H1_C$ demonstrated the relationship of facilitating value was significant toward DSCI (β = 0.127, t = 2.023, and p = 0.044). Correspondingly, hypothesis $H1_D$ execute that performance expectancy in predicting DSC intention and the relationship was substantial (β = 0.468, t = 0.086, and p = 0.000) and accepted in this study. $H1_E$ shows that trust significantly predict DSC intention and is supported in this study (β = 0.143, t = 1.683, and p = 0.043). Lastly, a similar result is seen in hypothesis H2. It is seen that the DSC Intention directly predict DSC Practice among the stakeholders of HEIs in Bangladesh with values β = 0.659, t = 16.328, and p = 0.000.

Table 4.10

Assessment of Path Model (Hypothesis Tests)

Hypothesis	**Relationships**	**Beta Values**	**SD**	***t* Values**	***p* Values**	**Findings**
$H1_A$	DL -> DSCI	0.043	0.052	0.819	0.041	Supported
$H1_B$	FC -> DSCI	0.083	0.050	1.638	0.012	Supported
$H1_C$	FV -> DSCI	0.127	0.063	2.023	0.044	Supported
$H1_D$	PE -> DSCI	0.468	0.086	5.446	0.000	Supported
$H1_E$	T -> DSCI	0.143	0.085	1.683	0.043	Supported
H2	DSCI -> DSCP	0.659	0.040	16.328	0.000	Supported

The data analysis validates and supports research hypotheses which evidently expresses that the digital literacy (DL), facilitating conditions (FC), facilitating value (FV), performance expectancy (PE) and Trust (T) have positive impact on digital supply chain (DSC) usage intention among higher education stakeholders in Bangladesh as a representative of least developed countries (LDCs). Moreover, their digital supply chain practice is also positively affected by their DSC usage intention. This finding of this study is in alignment with research conducted by other researchers previously. Büyüközkan and Göçer (2018) stated that an organization can extraordinarily fulfil stakeholders' satisfaction by adopting Digital Supply Chain (DSC) practices. Digitization provides higher transparency in the organization which leads to better decision making by providing more alternatives to the decision makers (Agrawal & Narain, 2018). According to Schrauf and Berttram (2016), Digital Supply Chains are more focused to the stakeholders and ensures higher agility and efficiency in its management. Stakeholders' perception of higher quality with the adoption of digital technologies is a driver for more flexible and improved supply chain management in the era of Industry 4.0 (Moeuf et al., 2017).

Aavakare, M. (2019) and Nikou and Aavakare (2021) conducted studies on user acceptable of technologies in learning environment and found that digital literacy has a positive and significant effect on users' intention to adopt digital technology. Similar results were also observed by Yu et al. (2021) where they found mobile literacy as a moderating factor while exploring behavioral intention to use a mobile health education website in Taiwan.

Moreover, reports of the United Nations and International Telecommunication Union show that among many aspects that contributes to the digitization drawback in countries like Bangladesh digital literacy is a prime one, particularly, at the individual stakeholder level. The more intellectually users find themselves improved in digital literacy, the more they engage in behavioral purposes. In this study, the test result of Hypothesis $H1_A$ states Digital literacy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh, which suggests that stakeholders' perceived competence in using digital technologies is a significant factor in their decision to adopt digital supply chain practices. This finding is consistent with previous studies that have identified digital literacy as a critical factor influencing the adoption of digital technologies. A higher level of digital literacy is a mandatory requirement among the teachers and learners of the education system today (Alexander et al., 2017; Chan et. a., 2017; Elgazzar & Elzarka, 2017). Least developed countries require more focus in digital literacy to educate their users in combination with increased affordability and accessibility to ensure higher inclusion rate in digital supply chain practices (International Telecommunication Union, 2020).

The test result of Hypothesis $H1_B$ states that Facilitating conditions positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh. Hence, facilitating condition is identified as a significant predictor of stakeholders' intention to adopt digital supply chain practices. The results suggest that stakeholders' perceived ease of use of digital supply chain practices is a crucial factor in their decision to adopt them. This finding aligns with previous studies that have identified the ease of use of new technologies as an important factor, like, studies conducted by Sharif et al. (2019) on the use of Learning Management System (LMS) among university students, Zhang et al. (2022) on the adoption of e-learning in Chinese college students, by Kencebay (2019) on the adoption of a mobile learning application using the UTAUT model found that facilitating conditions were positively related to users' behavioral intention.

The test result of Hypothesis $H1_C$ indicates that Facilitating value positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh which means facilitating value is a significant predictor of stakeholders' intention to adopt digital supply chain practices. This finding is aligned with previous studies that have also identified the perceived benefits of adopting new technologies as an important factor influencing the adoption decision. Alharbi et al. (2020) on the adoption of cloud-storage technologies among students in Malaysian HEIs, Eneizan et al. (2019) on the acceptance of mobile banking services, Chang et al. (2019) on the adoption of mobile payment services, have observed similar results that that consumers' willingness to accept and adopt new technology is significantly affected by the facilitating value. Facilitating Value has a significant positive effect on users' intention to adopt and use technology. This is an important finding and accurately assessed factor of this study, particularly in HEIs, which aids institutions in gaining a competitive advantage in the ever-evolving global market, adding value to the end-users.

The test result of Hypothesis $H1_D$ supports that Performance Expectancy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh. Similar results were observed by Lutfi et al. (2022) on the adoption of m-learning among university students of Saudi Arab, Jaradat et al. (2020) on the adoption of mobile health apps in Jordan, Eneizan et al. (2019) on users' intention to adopt mobile payment technology in Saudi Arabia found that performance expectancy was a significant predictor of users' intention to adopt new technology. Loureiro et al. (2018) also found that performance expectancy significantly influences consumers' intention to use online shopping platforms in Brazil, and like Jakkaew and Hemrungrote (2017) found a similar result in the adoption of mobile learning technology in Thailand.

Academicians choose to adopt emerging technologies more often if they feel such inventions are more advantageous and valuable in their everyday lives. Performance was already well-known as a more effective means to give universal access to a range of services for academicians in the HEIs. The results suggest that stakeholders' perceived usefulness of digital supply chain practices is a crucial factor in their decision to adopt them.

The test result of Hypothesis $H1_E$ states that Trust positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh. Trust is identified as a critical factor that positively influences stakeholders' intention to adopt digital supply chain practices which implies that higher education institutes need to establish trust with stakeholders by ensuring the security and confidentiality of data and information related to digital supply chain practices. The provision of transparent and reliable information regarding the adoption and implementation of digital supply chain practices can enhance the trust of stakeholders and encourage them to adopt these practices.

Earlier, many researchers observed similar results, like Al-Saedi et al. (2020)'s study on mobile payment, Akhter et al. (2020)'s research on Bangladeshi users to adopt mobile banking services, Kim et al. (2021)'s research on the adoption of online learning in Korean HEIs, Putri (2018)'s investigation on mobile banking services in Indonesia. The level of consumers' reliance on the integrity of the technology it promises to offer, trust is an integral component for establishing and maintaining a strong digital environment.

The test result of Hypothesis H2 identifies Digital Supply Chain usage intention positively affects the Digital Supply Chain practices of the HEI stakeholders in Bangladesh. It indicates that the role of DSC intention is highly meaningful in predicting DSCP. It implies that DSC intention is essential for strengthening DSCP for developing countries. This outcome is found to be steady with the previous research on DSCP in academia. Numerous researchers have investigated and found the similar results, like, Kao et al. (2019)'s research on wearable fitness tracker system using UTAUT2, Wu and Liu (2022)'s research on adoption of mobile payment, Alshammari et al. (2021)'s study on the adoption of e-health management in Saudi established that fact that the extent to which an individual will deliberately commit to be or not be a part of DSC usage it would significantly affect his/her ultimate DSC practices.

iv. Assessing the Level of Effect Size (f^2)

Hair et al. (2017) prescribed the level of effect size on endogenous constructs if the exogenous constructs are excluded from the model. As per their proposal, the values of f^2 above or equal to 0.35 should be considered as large, or around 0.15 considered as medium, or around 0.02 should be considered as small effects. The values of f^2 of the exogenous variable of this study are given in Table 4.11. It is found that modest effects were identified between five other constructs, such as digital literacy (DL), facilitating conditions (FC), facilitating value (FV), performance expectancy (PE) and Trust (T). Their values were 0.043, 0.083, 0.127, 0.468, and 0.143, respectively. DSC intention had significantly large effect (0.659) on the DSC practices among the HEI stakeholders of Bangladesh.

Table 4.11

Effect Size of Predictive Variables (f^2) on DSCP

Relationship	DSCI	DSCP	Magnitude
DSCI		0.659	Large
DL	0.043		Small
FC	0.083		Small
FV	0.127		Medium
PE	0.468		Large
T	0.143		Medium

v. Standardized Root Mean Square Residual (SRMR)

The SRMR is defined as the difference that exists between the observed correlation and the model implied correlation matrix. It allows to assess the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of (model) fit criterion. Its value less than 0.08 are considered as a good fit (Hair et al., 2021). According to Henseler et al. (2014), the SRMR is a goodness of fit measure for PLS-SEM that can be used to avoid model misspecification. Hair et al. (2021) also said that the SRMR value that less than 0.08 are considered a good fit for the model development using PLS-SEM. This SRMR value of this study is indicates a good fit of the model (Table 4.12).

vi. Normed Fit Index (NFI)

Hair et al. (2021) expressed that the NFI values closer to or above 0.9 usually represent an acceptable fit. The closer the value of NFI to 1, the better the model will be fit. The NFI value as presented in table 4.12 is evidence of acceptable fit of the model described in this study.

vi. Root Mean Square residual covariance (RMS $_{theta}$)

As presented in table 4.12, the observed RMS $_{theta}$ values is within the acceptable threshold (< 0.12) as introduced by Lohmöller (1989) and supported by Hair, et al. (2017).

Table 4.12

Model Fit

Standardized Root Mean Square Residual (SRMR)	0.054
Normed Fit Index (NFI)	0.856
Root Mean Square residual covariance (RMS $_{theta}$)	0.117

SRMR, NFI, and RMS $_{theta}$ values presented in this section are within the acceptable range for assessing the developed structure model as a fit model for the theory it is developed for. Hence, the strength and relationships among the exogenous variables and endogenous variables, digital literacy (DL), facilitating conditions (FC), facilitating value (FV), performance expectancy (PE) and Trust (T), digital supply chain usage intention (DSCI) and digital supply chain practice (DSCP) among the HEI stakeholders of Bangladesh are successfully modeled in this study. This fulfils the Research Objective 2 (RO2).

4.4.3 Assessment of Structural Model with Mediation

In this study, DSC usage intention of the stakeholders of higher education institutes of least developed countries was used as a mediator between digital literacy, facilitating condition, facilitating value, performance expectancy, trust, and DSC practice. Table 4.13 presents the data of mediation results of this study. The result shows mediation was found to be acceptable between digital literacy (DL) and DSC practice (DSCP). It was predicted that DSCI would mediate the relationship between DL and DSCP. The observed results in this study also found a significant result (β= 0.056, t= 2.376, and p < 0.018) for this relationship, which eventually supported the hypothesis $H3_A$. Subsequently, hypothesis $H3_B$ the mediator as DSCI, mediates the relationship between facilitating condition (FC) and DSCP (β= 0.062, t= 3.067 and p < 0.002). Similarly, a significant result is also observed for hypothesis $H3_C$ (β= 0.083, t= 3.311, and p < 0.001) on facilitating value (FV) being mediate through DSC intention. DSCI also remarkably mediates the effect of performance expectancy (PE) on DSCI as supported by hypothesis $H3_D$ (β= 0.275, t= 6.214, and p < 0.000). Lastly $H3_E$, the DSC intention mediates the relationship that is available between trust (T) and DSCP (β= 0.095, t= 2.253 and p < 0.012).

Table 4.13

Mediation effect of DSCI (Hypothesis Results)

Hypothesis	**Path**	**Beta Values**	**SD**	***t*- Values**	***p*- Values**	**Findings**
$H3_A$	DL -> DSCI -> DSCP	0.086	0.036	2.376	0.018	Supported
$H3_B$	FC -> DSCI -> DSCP	0.102	0.035	3.067	0.002	Supported
$H3_C$	FV -> DSCI -> DSCP	0.139	0.042	3.311	0.001	Supported
$H3_D$	PE -> DSCI -> DSCP	0.404	0.065	6.214	0.000	Supported
$H3_E$	T -> DSCI -> DSCP	0.214	0.095	2.253	0.012	Supported

The test results of Hypotheses $H3_A$, $H3_B$, $H3_C$, $H3_D$, $H3_E$ indicate that relationships of all the factors - Digital literacy (DL), Facilitating conditions (FC), Facilitating value (FV), Performance Expectancy (PE), and Trust (T) with the DSC Practice is mediated by DSC usage intention of the HEI stakeholders in Bangladesh. Research conducted by numerous researchers have also observed significant mediating effect of the user's usage intention on the factors that influences users' use behavior while accepting a new technology. Like, Wu et al. (2022)'s study on mobile health application adoption, Hammouri et al. (2021)'s study of mobile payment adoption, Parayil et al. (2022)'s research on mobile banking adoption in Maldives, Hafez and Amanullah (2021)'s investigation on mobile banking adoption in Bangladesh. These researchers observed full or partial mediating effect of user usage intention on the factors that influence them to adopt new technologies.

Same evidence was also presented by Raza et al. (2021) in their research in the context of mobile banking adoption in Pakistan where they examined the mediating effect of usage intention on the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit with use behavior. Similar results were observed by other researchers as well in their studies. Saengchai and Jermsittiparsert (2019) stated that digital supply chain practice (DSCP) among stakeholders ensures widespread availability of information, efficient collaboration and communications, which eventually results in increased agility, reliability and transparency (Saengchai & Jermsittiparsert, 2019).

A recent report of International Telecommunication Union (2020) identifies that the low digital literacy rate in combination with lack of adequate digital infrastructure in least developed countries is a reason of delayed progress towards industry 4.0. HEI stakeholders' perception towards digital supply chain practices in least developed countries as studied in this research also reflects the similar.

Data analysis of this section illustrates the fact that the studied factors - Digital literacy (DL), Facilitating conditions (FC), Facilitating value (FV), Performance Expectancy (PE) and Trust (T) which have impact on the Bangladeshi HEI stakeholder's adoption of Digital Supply Chain practices (DSCP) are all mediated by their DSC usage intention (DSCI). This evidently serves the Research Objective 3 (RO3) of this study.

4.5 Summary of Chapter

In this chapter, analytical methods were applied to conduct data analysis on the respondents' data based on the questionnaire survey collected from the HEI stakeholders of Bangladesh representing the LDCs. According to the evaluated results of the PLS-SEM measurement model and structural model, the 2 (two) hypotheses were conceptualized to test the relationship among the factors and their strength which influences the stakeholders of HEIs in Bangladesh to use and adopt Digital Supply Chain practices were supported. The relationships between the constructs and the indicator items that represent the constructs were analyzed based on the PLS-SEM outer model and the inner model illustrated the relationship among the constructs. The concept of the 3rd hypothesis was based on the mediation effect of the DSC usage intention on the latent variables towards adoption of DSC practices among the HEI stakeholders of LDCs. It was also tested and found to support as per the data analysis. The results as observed through the data analysis are summarized, and the discussion in Chapter Five follows.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The significant findings of the study are discussed in this chapter. This final chapter is organized into a total of seven sections. In section 5.2, a complete overview of the study is presented. A detailed discussion of the findings of this study is described in section 5.3. Various implications of this research are summarized in section 5.4. The contribution of this research is illustrated in section 5.5. Section 5.6 contains the limitations of this research, followed by conclusion and recommendations for future research in section 5.7.

5.2 Overview of the Study

The aim of this research is to develop a model of digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh representing least developed countries. To achieve this aim, this research determines the factors that can prescribe the practice of Digital Supply Chain (DSC) among the Bangladesh HEIs stakeholders, which are digital literacy (DL), facilitating condition (FC), facilitating value (FV), performance expectancy (PE) and trust (T). The association between these factors and the use intention of Digital Supply Chain (DSC) is also analyzed in this research. The research also examines the mediating effect of DSC use intention on the relationship that exists between the above-mentioned factors (independent variables) and the ultimate digital supply chain practices (DSCP) (dependent variable) in the HEIs of the LDCs. The research framework that has been developed in Chapter 3 portrays the relationship between DL, FC, FV, PE, T, DSCI, and DSCP. This relationship is also embedded with DSCI as the mediating variable. The Unified Theory of Acceptance and Use of Technology (UTAUT2) supports the framework. Further, questionnaire items were introduced and modified to ensure the study goals are linked through material validities and adapted through detailed literature analysis. A pilot study was then conducted to test the survey method among the stakeholders of higher education institutes in Bangladesh. The SmartPLS 4.0 statistical tools were used for the analysis.

Study goals outlined in Chapter 1 (one), as well as the literature on the factors mentioned in Chapter 2 (two), were used to ensure the main aim of the research to develop a model of digital supply chain's (DSC) general practices for higher education institutions (HEIs) from the stakeholders' perspective in Bangladesh representing least developed countries is achieved. As evident in Chapter 4 (Four), the study was quantitative in nature. The findings agreed with the theoretical context presented in the literature review section. A review of the findings of the study is followed by a list of factors that influence the stakeholders' intention and adoption of Digital Supply Chain Practices in the higher education institutes in the least developed countries. Next, the researcher looked into the strength and relationship among those factors and presented the relationship in the PLS-SEM model format along with specific quantities. Later, the researcher further measured the specific quantities of the mediating effect of HEI stakeholders' DSC use intention on the relationships of these factors with the ultimate DSC practices.

5.3 Discussion of the Findings

The ultimate findings of this study have been discussed in line with the objectives of the research, the research questions, and the hypotheses. In this study, Digital literacy (DL), facilitating condition (FC), facilitating value (FV), performance expectancy (PE) and trust (T) are the factors that influence Bangladesh HEI stakeholders' DSC usage intention (DSCI) towards adoption of DSC practice (DSCP) in the academia. The study also explores the mediating role of DSC usage intention on the connections among the identified factors (DL, FC, FV, PE, T) and DSC practice (DSCP).

5.3.1 The Direct Effect of Predictor Variables on the Mediator Variable

In this study, the hypothesis stating that "Digital literacy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh" was supported by the data analysis. This finding aligns with the existing literature on the importance of digital literacy in the context of technology acceptance and adoption.

Most of the respondents were university students within the age group of 19-25 who represent an important demographic group as they are the primary beneficiaries of digital technologies and play a significant role in driving technology adoption within educational settings. The next group - University teachers and administrators also contribute to shaping the adoption and implementation of Digital Supply Chain practices in HEIs with their perspectives and experiences. Even though the study included both male and female respondents, but the gender distribution is imbalanced with higher numbers from male group. It is important to acknowledge the gender dynamics and potential differences in digital literacy levels, which can influence the intention to use Digital Supply Chain practices. Future research could explore gender-specific factors and their impact on technology acceptance within the context of HEIs in Bangladesh. Moreover, respondents from families with lower incomes demonstrated a higher percentage in the sample. This suggests that digital literacy may be influenced by socioeconomic factors, and efforts to enhance digital literacy should consider the accessibility and affordability of digital resources, particularly in rural areas. Bridging the digital divide and promoting digital inclusion are critical for ensuring equitable access to technology and enabling the effective utilization of Digital Supply Chain practices in all HEIs.

Adopting digital literacy as a factor of the research framework for assessing users' intention to adopt DSC practices in HEI domain is a novelty of this research. In another research digital literacy factor was adopted with UTAUT framework was to find its influence on the use of digital portfolios in vocational training in Germany and as it was also found to have a positive impact like this study.

The supported hypothesis, indicating a positive relationship between digital literacy and the intention to use Digital Supply Chain practices, is justified by the fact that digital literacy is increasingly recognized as a necessary skill for navigating and leveraging digital technologies. By addressing the demographic factors and understanding their role in technology acceptance, HEIs can design effective strategies to foster digital literacy and promote the successful adoption and implementation of Digital Supply Chain practices, ultimately enhancing the overall performance and efficiency of higher education institutes in the least developed countries. In the context of Digital Supply Chain practices in Bangladeshi HEIs, stakeholders with higher levels of digital literacy are likely to have a better understanding of the tools, processes, and benefits associated with digital supply chain management. This understanding enhances their confidence and competence, leading to a higher intention to use Digital Supply Chain practices.

Digital literacy enables stakeholders to adapt to changing technological advancements and embrace new digital solutions aligning Bangladesh with global arena. Digital literacy enhances stakeholders' ability to effectively communicate, collaborate, and share information using digital platforms. Stakeholders with higher digital literacy of Bangladesh' HEIs are more likely to utilize digital tools for communication and collaboration, leading to increased intention to use Digital Supply Chain practices.

In the rapidly changing global landscape, digital supply chain management practices offer a competitive advantage to HEIs. Stakeholders of Bangladesh with higher digital literacy can harness the potential of digital supply chain technologies to enhance their institution's competitiveness. Recognizing the benefits and opportunities offered by digital supply chain practices, stakeholders are more likely to develop a positive intention to use these practices to gain a competitive edge.

The hypothesis stating that "Facilitating conditions positively affect the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh" was supported by the data analysis in this study. The findings suggest that the presence of facilitating conditions plays a significant role in shaping stakeholders' intention to use Digital Supply Chain practices in Higher Education Institutes (HEIs) in Bangladesh.

Examining the demographic characteristics of the respondents provides valuable insights into the sample composition and helps in understanding the relationship between facilitating conditions and the intention to use Digital Supply Chain practices. The majority of the respondents were university students within the age group 16-15 is a crucial demographic group as they are directly involved in the educational processes and can greatly influence the adoption and utilization of Digital Supply Chain practices followed by university teachers and administrators. Younger stakeholders may exhibit higher levels of digital readiness and adaptability, making them more receptive to facilitating conditions that support the use of Digital Supply Chain practices. However, it is essential to acknowledge the varying needs and expectations of stakeholders across different age groups and cater to their specific requirements in terms of training and support for adopting Digital Supply Chain practices. While gender distribution is imbalanced, gender inclusivity is vital for ensuring equal opportunities and promoting the intention to use Digital Supply Chain practices among all stakeholders. The diverse educational backgrounds contribute to a comprehensive understanding of the facilitating conditions required for the effective use of Digital Supply Chain practices. Stakeholders with higher levels of education have a greater capacity to comprehend and utilize the resources and systems involved in Digital Supply Chain practices. The majority of the respondents are reported from lower family income level. To promote the intention to use Digital Supply Chain practices, it is important to consider the affordability and accessibility of resources, particularly for stakeholders with lower family incomes.

The supporting evidence for the hypothesis can be attributed to several factors. First, facilitating conditions refer to the availability of resources, support, and infrastructure necessary for the effective adoption and utilization of Digital Supply Chain practices. Stakeholders who have access to adequate resources, including technology, training programs, and support systems, are more likely to develop a positive intention to use Digital Supply Chain practices.

Second, the presence of facilitating conditions can enhance stakeholders' confidence and self-efficacy in utilizing Digital Supply Chain practices. When stakeholders perceive that the necessary conditions are in place, such as training programs, technical assistance, and supportive organizational structures, they are more likely to feel empowered and motivated to engage with Digital Supply Chain practices.

Third, facilitating conditions play a crucial role in mitigating barriers and challenges associated with the adoption of Digital Supply Chain practices. For example, providing access to training programs and technical support can help stakeholders overcome technological barriers and enhance their skills and knowledge, thereby increasing their intention to use Digital Supply Chain practices.

Findings of the study suggest that the presence of facilitating conditions significantly influences stakeholders' intention to use Digital Supply Chain practices in HEIs in Bangladesh. Similar correlations of facilitating condition with usage intention while adopting new technology has been observed by most of the researchers in different domains and geography.

The hypothesis stating that "Facilitating value positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh" was supported by the data analysis in this study. The findings suggest that the perceived value associated with Digital Supply Chain practices significantly influences stakeholders' intention to use these practices in Higher Education Institutes (HEIs) of Bangladesh.

As the majority of the respondents were university students and within the young age group, the primary beneficiaries of education, their positive perception of the value and benefits offered by these practices significantly impact their intention to use them. University teachers and administrators' contribution is in shaping the perceived value and creating an enabling environment for the adoption of Digital Supply Chain practices in HEIs. While gender imbalance exists, it is important to ensure equal access to information and opportunities for all stakeholders. Regarding educational qualifications, the majority of the respondents held bachelor's degrees and higher level of education often correlate with a better understanding of the value proposition of Digital Supply Chain practices. Stakeholders with advanced degrees may recognize the potential for efficiency, collaboration, and improved decision-making that can be achieved through the adoption of these practices. This recognition contributes to their intention to use Digital Supply Chain practices in HEIs. As expected from Bangladesh, or any other least developed countries, stakeholders with lower family incomes may have a higher propensity to appreciate the value of Digital Supply Chain practices, as these practices can provide cost-saving opportunities and improve access to resources. Urban stakeholders, who typically have better access to resources and technology, may recognize the value of these practices more readily. However, efforts should be made to ensure that stakeholders from suburban and rural areas also perceive and appreciate the value of Digital Supply Chain practices, as these practices can contribute to bridging the digital divide and promoting educational equity.

Facilitating value refers to the perceived benefits, advantages, and positive outcomes associated with the adoption and use of Digital Supply Chain practices. Stakeholders who recognize the value of these practices, such as improved efficiency, collaboration, enhanced decision-making, and access to resources, are more likely to develop a positive intention to use them. The perception of value is influenced by stakeholders' awareness and understanding of the potential benefits of Digital Supply Chain practices. Stakeholders with higher levels of education and exposure to digital technologies are more likely to appreciate the value of these practices and understand how they can positively impact their academic and professional lives. Moreover, the alignment between stakeholders' needs and the value proposition of Digital Supply Chain practices is crucial. When stakeholders perceive that these practices address their specific challenges, provide solutions, and offer tangible benefits, their intention to use them is strengthened. Majority researchers also observed similar correlation of facilitating value with usage intention among the users while adopting technology.

The hypothesis stating that "Performance Expectancy positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh" was supported in this study which indicates that stakeholders' perception of the expected benefits and positive outcomes associated with Digital Supply Chain practices significantly influences their intention to use these practices in Higher Education Institutes (HEIs) of Bangladesh.

Analyzing the demographic characteristics of the respondents provides valuable insights into the sample composition and helps in understanding the relationship between performance expectancy and the intention to use Digital Supply Chain practices. Once again, the major respondents were young university students, who are the primary beneficiaries of education. Their perception of the expected performance benefits of Digital Supply Chain practices greatly influences their intention to use them. They perceive these practices as tools that can enhance their academic performance, improve efficiency, and facilitate collaboration. The perception of these expected benefits positively influences their intention to use Digital Supply Chain practices. Stakeholders with higher levels of education often possess a broader perspective and deeper understanding of the potential performance benefits associated with Digital Supply Chain practices. They can recognize the value of these practices in enhancing decision-making processes, streamlining supply chain operations, and improving overall performance outcomes in HEIs. In this study, the majority of respondents are from Urban stakeholders, who typically have better access to resources and technology, and may more readily recognize the expected performance benefits of Digital Supply Chain practices. However, it is crucial to ensure that stakeholders from suburban and rural areas also perceive and appreciate the expected performance benefits, as these practices can contribute to bridging the digital divide and improving educational outcomes across different regions.

Performance expectancy refers to stakeholders' perceptions of the expected positive outcomes and benefits associated with using Digital Supply Chain practices. In this study, stakeholders who perceive that these practices can enhance their academic performance, improve efficiency, facilitate collaboration, and streamline supply chain processes are more likely to develop a positive intention to use them. When stakeholders recognize that these practices address their specific challenges, provide solutions, and offer tangible benefits, their intention to use them is strengthened. The perception of expected performance benefits is influenced by stakeholders' awareness and understanding of how Digital Supply Chain practices can positively impact their academic and professional lives. Stakeholders with higher levels of education and exposure to digital technologies are more likely to appreciate the potential benefits and performance enhancements that can be achieved through the adoption of these practices. The study findings highlight the importance of performance expectancy in shaping stakeholders' intention to use Digital Supply Chain practices in HEIs in Bangladesh.

Similar observations were found in most of other research where performance expectancy is positively affects the adoption of digitization, more particularly in developing and under-developed countries, where economic and technological challenges are prevalent. The possibility of elevated productivity, quickened task completion, enhanced work efficiency, heightened task precision, and improved individual performance drives users strongly for seeking to overcome the constraints imposed by limited resources and infrastructural deficiencies.

The hypothesis, "Trust positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh", was also supported by the data analysis in this study. The findings suggest that the level of trust stakeholders have in the context of Digital Supply Chain practices significantly influences their intention to use these practices in Higher Education Institutes (HEIs) of Bangladesh.

The major section of respondents of the study are young university students, one of the main stakeholder groups of the research domain - HEIs, exhibited that trust plays an important role in their decision-making process, as they rely on the trustworthiness of the digital platforms and systems they interact with. Trust in the security, reliability, and privacy of Digital Supply Chain practices can significantly impact their intention to use these practices. Younger stakeholders, who have grown up in the digital age, have a higher level of trust in technology and digital platforms. Their familiarity with digital tools and their trust in online transactions and interactions can positively influence their intention to use Digital Supply Chain practices. The second major group of respondents is comprised of university teachers and administrators who also rely on trust for adopting DSC practices in HEIs. The demographic also reflected that stakeholders with higher levels of education often have a better understanding of technology and digital platforms, which can contribute to their trust in Digital Supply Chain practices. They may be more confident in the reliability and security of these practices, thereby strengthening their intention to use them. Considering family income, the findings indicate that a significant proportion of respondents reported lower family income levels. Trust becomes particularly important for stakeholders with limited financial resources, as they may rely on digital platforms to access resources and services. Building trust in Digital Supply Chain practices can alleviate concerns related to the security and reliability of online transactions and interactions, ultimately increasing stakeholders' intention to use these practices. Moreover, urban stakeholders, who typically have better access to technology and digital infrastructure, may have a higher level of trust in these practices.

The support of the hypothesis can be contributed to several reasons. First, trust is a fundamental factor in technological acceptance and adoption. Stakeholders who perceive Digital Supply Chain practices as reliable, secure, and trustworthy are more likely to develop a positive intention to use them. Second, trust is closely linked to stakeholders' perceptions of privacy, security, and data protection. Trustworthy practices in managing personal information and ensuring the privacy and security of digital transactions can enhance stakeholders' trust in Digital Supply Chain practices. Third, trust is built through positive experiences, transparency, and effective communication. When stakeholders have positive experiences with Digital Supply Chain practices, such as seamless transactions, prompt service, and clear communication, their trust in these practices is strengthened.

The study highlights the importance of trust in shaping stakeholders' intention to use Digital Supply Chain practices in HEIs in Bangladesh. Other researchers who have conducted similar studies in different geographical areas, like, Vietnam, Indonesia, South Korea, etc. found that trust significantly influences the adoption of digital technology in varieties of domains.

5.3.2 The Direct Relationship between the Mediator (DSCI) and the Dependent Variable (DSCP)

The hypothesis stating that "Digital Supply Chain usage intention positively affects the Digital Supply Chain usage intention of the HEI stakeholders in Bangladesh" was supported by the data analysis in this study. The findings suggest that the intention to use Digital Supply Chain practices among stakeholders in Higher Education Institutes (HEIs) in Bangladesh has a positive influence on their actual usage of these practices.

There are several reasons behind the support for this hypothesis. Stakeholders' intention to use Digital Supply Chain practices reflects their recognition of the benefits and value offered by these practices. They perceive Digital Supply Chain practices as tools that can enhance their educational experience, facilitate collaboration, and improve efficiency. Secondly, the demographic characteristics of the respondents, such as their roles as students, teachers, and administrators, contribute to their positive intention to use and actual usage of Digital Supply Chain practices. Students, being at the forefront of the education system, drive the adoption and usage of these practices.

Young university students, most of the respondents of this study, who plays a significant role in driving the adoption and usage of Digital Supply Chain practices in HEIs, have positive intention to use Digital Supply Chain practices which influences their actual usage of DSC practices. They perceive these practices as valuable and beneficial to their academic pursuits as they actively engage in various academic activities and utilize digital tools and platforms to access resources, collaborate with peers, and participate in online learning environments. So did the university teachers and administrators, respectively. Their role in promoting and supporting the adoption of Digital Supply Chain practices within the HEIs is also crucial. Their intention to use these practices influences their behavior and can lead to the establishment of a supportive environment that encourages other stakeholders to adopt and utilize Digital Supply Chain practices. Teachers and administrators play a crucial role in creating an enabling environment that encourages the utilization of Digital Supply Chain practices within HEIs.

5.3.3 The Mediating Relationship Between the Predictor Variable and the Dependent Variable

Hypotheses relevant to the mediation of DSC usage intention on all the relationships among the factors of this study - Facilitating Value, Facilitating Condition, Digital Literacy, Performance Expectancy and Trust towards DSC Practice was supported in the domain of HEIs in the context of Bangladesh.

The majority of the respondents were young university students who are often digital natives, having grown up in the digital era, and are more likely to possess a higher level of Digital literacy. They are familiar with technology and digital tools, which enhances their ability to engage with and utilize DSC practices. This group consists of young and tech-savvy individuals who are typically more receptive to technological advancements and innovations. Their familiarity and comfort with digital tools and technologies may positively influence their perception of facilitating value, performance expectancy, trust, and utilization of facilitating conditions. Their positive intention to use DSC practices serves as a mediator between these factors and the actual usage of these practices. Younger stakeholders may perceive DSC practices as valuable in improving their educational experience and future career prospects, thus mediating the relationship all of the previous factors with DSC practice adoption.

University teachers and administrators constituted the next group of respondents. These stakeholders also play a significant role in shaping the DSC practices within HEIs. Their Digital literacy influences their intention to adopt DSC practices, as they recognize the value and benefits of DSC practices, they actively promote and implement these practices within the educational context. The level of education can impact individuals' understanding of facilitating conditions, facilitating value, trust and performance expectancy and their ability to leverage them effectively. Higher levels of education are often associated with a broader knowledge base and a better understanding of the benefits and potential of DSC practices. This, in turn, enhance the mediation effect of DSC usage intention on the relationship between all these factors and DSC practice adoption.

Gender can influence Digital literacy levels, with studies suggesting that males may exhibit higher levels of Digital literacy compared to females. However, it is essential to note that the relationship between Digital literacy, DSC usage intention, and the actual usage of DSC practices may not be directly influenced by gender alone but rather by the underlying factors associated with Digital literacy. Factors such as educational background, exposure to technology, and digital skills development can contribute to the gender differences observed. Similar observations are also valid for factors like, facilitating condition, facilitating value, performance expectancy and trust.

Even though majority of the respondents are from urban area, but most of their income level is reported lower, which is very much likely in the context of Bangladesh. Digital literacy levels can be influenced by socioeconomic factors, including access to technology and digital resources. Lower family income may limit access to technology and training opportunities, potentially impacting Digital literacy levels, affordability for facilitating condition and facilitating value, reliability on performance and deposition on trust. However, despite these challenges, the positive intention to use DSC practices among stakeholders demonstrates their recognition of the value and importance of these practices in enhancing educational processes.

Most of the researchers identified usage intention as a mediator on the relationships of various factors with use behavior while adopting technology. Like, adoption of internet banking, mobile health apps, mobile banking in Jordan, e-government services in India, internet banking in Pakistan, mobile payment, mobile banking in China, e-health management, mobile payment in Saudi Arabia. Lately, numerous research were conducted on mobile payment adoption in various countries, even in Bangladesh, and similar mediation effect of usage intention was observed by the researchers on the factors towards use behavior. Moreover, there were research in the similar domain of HEIs for adoption of other technologies, like, usage of Moodle among Jordanian university students, usage of MOOCs among Malaysian students, online learning in South Korean HEI, m-learning in Saudi university, e-learning in Chinese and UAE university. All research observed significant mediation effect of users use intention on the relationships of various factors with the use behavior while adopting new technology. The finding of this study as supported by the hypotheses stated above also resonates with this fact.

5.4 Implications of the Study

The implication of this research is illustrated in two dimensions – Theoretical and Practical - as presented below.

5.4.1 Theoretical Implication

According to a theoretical perspective, this empirical research has had a substantial impact in several ways. First and foremost, Venkatesh et al. (2012) have created the 'Unified Technology Acceptance and Use of Technology 2 (UTAUT 2)' (Venkatesh et al., 2012) as a founding theory for the study of technology acceptance and usage. From a theoretical aspect, it is anticipated that the research will substantially impact UTAUT 2. Similar to Venkatesh et al. (2012), this theory was applied to relationship analysis, namely factors that influence stakeholders' digital supply chain practice in higher education institutions in Bangladesh.

The findings of this study suggest that digital literacy (DL), facilitating condition (FC), facilitating value (FV), performance expectancy (PE), and trust (T) significantly influence stakeholders' intention to adopt digital supply chain practices. The theoretical implications of this research can be discussed in relation to the UTAUT2 model, which provides a comprehensive framework for understanding the adoption of new technologies.

Firstly, a novel theoretical implication of this research in incorporation of Digital Literacy as a construct in predicting stakeholders' intention to adopt digital supply chain practices. The results suggest that stakeholders' perceived competence in using digital technologies is a significant factor in their decision to adopt digital supply chain practices. The adoption of this construct in the UTAIUT2 model is a significant theoretical implication justified by available literature studies as illustrated in chapter

2, particularly, in the context of technological acceptance among stakeholders of Bangladesh as a representative of least developed countries.

Moreover, this research identifies facilitating condition, facilitating value, performance expectancy and trust as other crucial constructs and significant predictors of stakeholders' intention to adopt digital supply chain practices. This finding aligns with previous studies that have identified the ease of use, perceived usefulness, competence, benefits and belief in new technologies as important factors influencing the adoption decision.

5.4.2 Practical Implication

The findings of the research highlight the importance of digital literacy (DL) as a significant factor in determining stakeholders' intention to adopt digital supply chain practices in higher education institutes. This implies that education and training programs should be designed and implemented to enhance the digital literacy skills of stakeholders, including faculty members, students, and administrative staff, to effectively utilize digital supply chain practices. This would require the allocation of resources to provide access to digital technology and training programs to enhance digital literacy skills.

Apart from that, facilitating conditions (FC), facilitating value, performance expectancy and trust were identified as a crucial factor that influences stakeholders' intention to adopt digital supply chain practices. This implies that higher education institutes in least developed countries need to provide a supportive environment to encourage the adoption of digital supply chain practices. The provision of necessary infrastructure, such as high-speed internet, computer hardware, and software, along with adequate training and support services, are critical in this regard.

These findings can help practitioners and policymakers to develop strategies that promote the adoption of digital technologies in supply chain management in higher education institutes of the least developed countries.

5.5 Contribution of the study

This research has made significant contributions to the understanding of factors that influence the adoption and implementation of Digital Supply Chain (DSC) practices in Higher Education Institutes (HEIs) in Least Developed Countries (LDCs), particularly in Bangladesh. The study has successfully employed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to identify key influencing factors, including Digital Literacy (DL), Facilitating Conditions (FC), Facilitating Value (FV), Performance Expectancy (PE), and Trust (T). Moreover, the research has demonstrated that DSC usage intention mediates the relationship between these factors and the actual DSC use behavior among stakeholders in Bangladeshi HEIs. By supporting all eleven hypotheses, the study has laid the foundation for further research, policy-making, and practical interventions in the area of DSC practices in LDCs.

It also underscores the need to consider the unique challenges faced by LDCs, such as limited resources, inadequate infrastructure, and lack of digital literacy, when designing interventions to promote DSC adoption in the higher education sector. The study provides a roadmap for the development of targeted interventions aimed at enhancing the adoption and implementation of DSC in HEIs. The findings can inform the design of capacity-building programs, infrastructure development initiatives, and policy reforms that support the integration of DSC practices into the higher education sector in LDCs.

This study can provide further insights into the work and functionality of DSCs, specifically reformed and restructured in HEIs, that can go on to serve as the blueprint for mapping out the process and pathway for other service and non-profit-oriented organizations in the future, particularly in the LDC countries. The developed model of factors that influence the DSC practices in HEIs indicates that Trust is the major influencing variable, followed by Performance Expectancy, Facilitating Value, Facilitating Conditions, and Digital Literacy.

Former research indicates that the evolution of SCs is not merely because of the implementation of technology in traditional SC systems but rather because of a cultural change within the business operations and its management through digitalization, through which each component evolves and transforms into a cohesive DSC. But, with little to no concrete or comprehensive research conducted previously on identifying factors that influence the HEI stakeholders and the role or correlation of these factors in DSCs in HEIs, its implications were yet to be explored. This created the scope for the study and added value to its findings to initiate bridging the preexisting gap between SCM and HEIs. Shifting from a traditional SC into a digital one, as crucial as it may be, comes with its own territory of challenges. And over time, as DSC evolves, so must the variants and their implications to the overall SCM in HEIs. It is a continuous cyclical process as new sources of information will emerge, new analytical tools will be developed, and new technology, demands, people, and risks will always evolve. And HEIs are to do the same if they wish to thrive instead of merely surviving. This study contributes as a stepstone towards this transformation.

A major contribution of this study is its geographical scope, HEIs of Bangladesh representing LDCs. While DSC has long been a reality in developed countries around the world, it is still a novel concept in emerging nations, where sectors, including education, are constrained by limited resources. DSC is relatively new, even in the manufacturing and service industries of Bangladesh, making it completely unchartered territory when it comes to the education sector. The findings of this study would also aid in bridging that gap. The majority of the HEIs in Bangladesh, as well as other under-developed or developing countries, are only just beginning to embrace digitalization in education, still adapting to multimedia classroom applications and use of the Internet in preparing lectures and assignments. With information technology connecting students, faculty members, and administrative officials, as well as elaborate processes and enhanced communication, digitalizing the academic SC has become the most significant practice in HEIs today. With the help of the factors and correlations identified in this study, future researchers conducting studies in this similar domain and scope can be more cohesive to their goals.

5.6 Recommendations

Based on the research findings, the following recommendations are made to enhance the adoption and implementation of DSC practices in HEIs in Bangladesh and other LDCs:

5.6.1 Enhance Digital Literacy

Improving digital literacy among HEI stakeholders is paramount for the successful adoption of DSC practices. Institutions should offer training programs and workshops, integrate digital literacy into the curriculum, and foster a culture of lifelong learning to ensure that stakeholders have the necessary skills to leverage digital technologies effectively.

5.6.2. Establish Facilitating Conditions

HEIs should work towards creating an environment that supports the adoption of DSC practices. This includes investing in infrastructure, providing access to resources, and ensuring the availability of technical support. Institutions should also collaborate with industry partners, government agencies, and non-governmental organizations to enhance their capabilities and resources.

5.6.3. Promote Facilitating Value

To foster a sense of value in the adoption of DSC practices, HEIs should emphasize the benefits of these practices, such as cost reduction, improved efficiency, and enhanced collaboration among stakeholders. Institutions should also highlight the competitive advantage gained from adopting DSC practices, particularly in the context of globalization and the increasing demand for digitally competent graduates.

5.6.4. Enhance Performance Expectancy

HEIs should actively communicate the potential benefits of DSC practices to their stakeholders to raise performance expectancy. This can be achieved through awareness campaigns, success stories, and showcasing the positive impact of DSC on other institutions. Additionally, institutions should set realistic expectations and provide ongoing support to ensure that stakeholders can achieve the desired outcomes from DSC practices.

5.6.5. Build Trust

Trust is a critical factor in the adoption of new technologies, particularly in LDCs where stakeholders may have limited exposure to digital technologies. HEIs should take measures to build trust among their stakeholders by ensuring data privacy, maintaining transparency in DSC practices, and addressing potential risks associated with the use of digital technologies. Institutions should also engage in open dialogue with stakeholders to address their concerns and foster a sense of shared ownership in the DSC implementation process.

5.6.6. Strengthen DSC Usage Intention

As DSC usage intention mediates the relationship between the identified factors and actual DSC use behavior, HEIs should focus on strengthening stakeholders' intention to use DSC practices. This can be achieved by addressing the barriers to adoption, providing ongoing support, and ensuring that stakeholders are equipped with the necessary skills and resources to effectively engage with DSC practices.

5.6.7. General Recommendations for LDCs

While this study focused on Bangladesh, the findings and recommendations can also be applied to other LDCs facing similar challenges in adopting DSC practices.

Policymakers and HEI administrators in these countries should consider implementing the recommendations outlined above to facilitate the adoption and implementation of DSC practices and enhance the overall performance of their higher education sector.

5.7 Limitations

The research focused on Bangladesh, and while the findings may be applicable to other LDCs, it is essential to conduct similar studies in other contexts to enhance the generalizability of the results. Second, the study employed a cross-sectional design, which limits the ability to establish causality between the factors and DSC use behavior. Future research could employ longitudinal designs to better understand the causal relationships and the dynamics of DSC adoption over time. Third, this study focused on the UTAUT2 model; other technology acceptance models, such as the Technology Acceptance Model (TAM) or the Diffusion of Innovations (DOI) theory, could be employed in future research to provide additional insights into the factors influencing DSC adoption.

Furthermore, future research could explore the role of other factors, such as organizational culture, leadership, and external pressures, in shaping the adoption of DSC practices in HEIs. Another potential avenue for future research is to investigate the impact of DSC practices on educational outcomes, such as student performance and satisfaction, faculty performance, and institutional competitiveness. Lastly, future studies could also examine the role of government policies and interventions in facilitating the adoption and implementation of DSC practices in HEIs in LDCs.

5.8 Conclusions

This research has successfully provided insights into the factors that influence Digital Supply Chain (DSC) practices in Higher Education Institutes (HEIs) in Least Developed Countries (LDCs), with a particular focus on Bangladesh. Using the UTAUT2 model, the study identified Digital Literacy (DL), Facilitating Conditions (FC), Facilitating Value (FV), Performance Expectancy (PE), and Trust (T) as crucial determinants of DSC usage intention among stakeholders. Moreover, it was found that DSC usage intention mediates the relationship between these factors and the actual DSC use behavior. All eleven hypotheses of the study were supported, validating the proposed relationships and suggesting that these factors play a significant role in shaping the adoption and implementation of DSC practices in HEIs in Bangladesh.

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APPENDIX A.

PARTIAL LEAST SQUARE STRUCTURAL EQUATION MODELING (PLS-SEM) DATA ANALYSIS USING SMARTPLS 3.0

Table A.1

Path Coefficients among constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	0.052	0.819	0.041
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	0.050	1.638	0.012
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	0.063	2.023	0.044
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.086	5.446	0.000
Trust -> Digital Supply Chain Intention	0.143	0.138	0.085	1.683	0.043
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.040	16.328	0.000

Table A.2

Confidence Intervals (Path Coefficients)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	-0.067	0.146
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.582	0.744

Table A.2 continued

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	-0.007	0.190
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	0.015	0.254
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.307	0.647
Trust -> Digital Supply Chain Intention	0.143	0.138	-0.047	0.303

Table A.3

Confidence Intervals Bias Corrected (Path Coefficients)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	0.002	-0.069	0.140
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.004	0.577	0.736
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	-0.001	-0.003	0.195
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	-0.003	0.030	0.279
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.008	0.302	0.645
Trust -> Digital Supply Chain Intention	0.143	0.138	-0.005	-0.045	0.305

Table A.4

Total Indirect Effects among constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	0.036	0.778	0.018
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.053	0.035	1.542	0.002
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	0.042	2.000	0.001
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.065	4.753	0.000
Trust -> Digital Supply Chain Practice	0.094	0.091	0.095	0.989	0.012

Table A.5

Confidence Intervals (Total Indirect Effects)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	-0.043	0.097
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.054	-0.005	0.127
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	0.010	0.162
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.196	0.453
Trust -> Digital Supply Chain Practice	0.094	0.091	-0.033	0.200

Table A.6

Confidence Intervals Bias Corrected (Total Indirect Effects)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	0.002	-0.045	0.095
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.054	0.000	-0.003	0.131
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	-0.002	0.018	0.185
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.008	0.182	0.437
Trust -> Digital Supply Chain Practice	0.094	0.091	-0.003	-0.026	0.205

Table A.7

Specific Indirect Effects among constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Digital Literacy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.086	0.087	0.036	2.376	0.018
Facilitating Condition -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.102	0.101	0.035	3.067	0.002
Facilitating Value -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.139	0.141	0.042	3.311	0.001

Table A.7 continued

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Performance Expectancy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.404	0.403	0.065	6.214	0.000
Trust -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.214	0.211	0.095	2.253	0.012

Table A.8

Confidence Intervals (Specific Indirect Effects)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Facilitating Value -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.084	0.082	0.010	0.162
Digital Literacy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.028	0.030	-0.043	0.097
Performance Expectancy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.309	0.317	0.196	0.453
Trust -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.094	0.091	-0.033	0.200
Facilitating Condition -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.054	0.054	-0.005	0.127

Table A.9

Confidence Intervals Bias Corrected (Specific Indirect Effects)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
Facilitating Value -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.084	0.082	-0.002	0.018	0.185
Digital Literacy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.028	0.030	0.002	-0.045	0.095
Performance Expectancy -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.309	0.317	0.008	0.182	0.437
Trust -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.094	0.091	-0.003	-0.026	0.205
Facilitating Condition -> Digital Supply Chain Intention -> Digital Supply Chain Practice	0.054	0.054	0.000	-0.003	0.131

Table A.10

Total Effects among constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	0.052	0.819	0.041
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	0.035	0.814	0.041

Table A.10 continued

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.040	16.328	0.000
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	0.050	1.638	0.010
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.054	0.034	1.592	0.012
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	0.063	2.023	0.044
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	0.042	2.017	0.044
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.086	5.446	0.000
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.065	4.740	0.000
Trust -> Digital Supply Chain Intention	0.143	0.138	0.085	1.683	0.043
Trust -> Digital Supply Chain Practice	0.094	0.091	0.056	1.678	0.044

Table A.11

Confidence Intervals (Total Effects)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	-0.067	0.146

Table A.11 continued

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	-0.043	0.097
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.582	0.744
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	-0.007	0.190
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.054	-0.005	0.127
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	0.015	0.254
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	0.010	0.162
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.307	0.647
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.196	0.453
Trust -> Digital Supply Chain Intention	0.143	0.138	-0.047	0.303
Trust -> Digital Supply Chain Practice	0.094	0.091	-0.033	0.200

Table A.12

Confidence Intervals Bias Corrected (Total Effects)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Intention	0.043	0.045	0.002	-0.069	0.140

Table A.12 continued

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
Digital Literacy -> Digital Supply Chain Practice	0.028	0.030	0.002	-0.045	0.095
Digital Supply Chain Intention -> Digital Supply Chain Practice	0.659	0.663	0.004	0.577	0.736
Facilitating Condition -> Digital Supply Chain Intention	0.083	0.082	-0.001	-0.003	0.195
Facilitating Condition -> Digital Supply Chain Practice	0.054	0.054	0.000	-0.003	0.131
Facilitating Value -> Digital Supply Chain Intention	0.127	0.124	-0.003	0.030	0.279
Facilitating Value -> Digital Supply Chain Practice	0.084	0.082	-0.002	0.018	0.185
Performance Expectancy -> Digital Supply Chain Intention	0.468	0.476	0.008	0.302	0.645
Performance Expectancy -> Digital Supply Chain Practice	0.309	0.317	0.008	0.182	0.437
Trust -> Digital Supply Chain Intention	0.143	0.138	-0.005	-0.045	0.305
Trust -> Digital Supply Chain Practice	0.094	0.091	-0.003	-0.026	0.205

Table A.13

Outer Loadings of predictive items on the constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
DL1 <- Digital Literacy	0.717	0.718	0.035	20.382	0.000
DL2 <- Digital Literacy	0.842	0.840	0.021	39.960	0.000
DL3 <- Digital Literacy	0.842	0.840	0.017	49.177	0.000
DL4 <- Digital Literacy	0.777	0.778	0.027	29.011	0.000
DL5 <- Digital Literacy	0.579	0.581	0.047	12.317	0.000
DSCI1 <- Digital Supply Chain Intention	0.826	0.825	0.028	29.969	0.000
DSCI2 <- Digital Supply Chain Intention	0.601	0.601	0.049	12.231	0.000
DSCI3 <- Digital Supply Chain Intention	0.817	0.816	0.028	29.457	0.000
DSCI4 <- Digital Supply Chain Intention	0.851	0.851	0.017	48.677	0.000
DSCI5 <- Digital Supply Chain Intention	0.791	0.791	0.040	19.787	0.000
DSCP1 <- Digital Supply Chain Practice	0.912	0.911	0.016	56.957	0.000
DSCP2 <- Digital Supply Chain Practice	0.942	0.942	0.011	89.494	0.000
DSCP3 <- Digital Supply Chain Practice	0.944	0.944	0.008	112.429	0.000
DSCP4 <- Digital Supply Chain Practice	0.917	0.916	0.018	50.750	0.000
DSCP5 <- Digital Supply Chain Practice	0.916	0.915	0.016	57.483	0.000
FC1 <- Facilitating Condition	0.750	0.750	0.039	19.114	0.000

Table A.13 continued

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
FC2 <- Facilitating Condition	0.776	0.775	0.033	23.195	0.000
FC3 <- Facilitating Condition	0.834	0.835	0.027	31.097	0.000
FC4 <- Facilitating Condition	0.842	0.841	0.025	34.334	0.000
FC5 <- Facilitating Condition	0.807	0.807	0.023	35.871	0.000
FV1 <- Facilitating Value	0.738	0.738	0.039	19.131	0.000
FV2 <- Facilitating Value	0.838	0.837	0.022	38.602	0.000
FV3 <- Facilitating Value	0.848	0.848	0.018	45.859	0.000
FV4 <- Facilitating Value	0.755	0.753	0.037	20.486	0.000
PE1 <- Performance Expectancy	0.878	0.878	0.018	47.537	0.000
PE2 <- Performance Expectancy	0.899	0.899	0.018	49.208	0.000
PE3 <- Performance Expectancy	0.935	0.935	0.008	111.570	0.000
PE4 <- Performance Expectancy	0.862	0.861	0.023	37.042	0.000
PE5 <- Performance Expectancy	0.867	0.868	0.022	38.690	0.000
T1 <- Trust	0.895	0.894	0.013	70.196	0.000
T2 <- Trust	0.889	0.888	0.015	59.433	0.000
T3 <- Trust	0.641	0.641	0.046	13.890	0.000
T4 <- Trust	0.761	0.761	0.030	24.968	0.000
T5 <- Trust	0.850	0.850	0.020	41.665	0.000

Table A.14

Confidence Intervals (Outer Loadings)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
DL1 <- Digital Literacy	0.717	0.718	0.649	0.780
DL2 <- Digital Literacy	0.842	0.840	0.796	0.877
DL3 <- Digital Literacy	0.842	0.840	0.804	0.872
DL4 <- Digital Literacy	0.777	0.778	0.723	0.826
DL5 <- Digital Literacy	0.579	0.581	0.481	0.667
DSCI1 <- Digital Supply Chain Intention	0.826	0.825	0.765	0.873
DSCI2 <- Digital Supply Chain Intention	0.601	0.601	0.489	0.684
DSCI3 <- Digital Supply Chain Intention	0.817	0.816	0.759	0.866
DSCI4 <- Digital Supply Chain Intention	0.851	0.851	0.817	0.883
DSCI5 <- Digital Supply Chain Intention	0.791	0.791	0.706	0.858
DSCP1 <- Digital Supply Chain Practice	0.912	0.911	0.874	0.938
DSCP2 <- Digital Supply Chain Practice	0.942	0.942	0.920	0.960
DSCP3 <- Digital Supply Chain Practice	0.944	0.944	0.926	0.959
DSCP4 <- Digital Supply Chain Practice	0.917	0.916	0.874	0.946
DSCP5 <- Digital Supply Chain Practice	0.916	0.915	0.881	0.942
FC1 <- Facilitating Condition	0.750	0.750	0.675	0.820
FC2 <- Facilitating Condition	0.776	0.775	0.703	0.830
FC3 <- Facilitating Condition	0.834	0.835	0.778	0.881
FC4 <- Facilitating Condition	0.842	0.841	0.790	0.886
FC5 <- Facilitating Condition	0.807	0.807	0.759	0.844
FV1 <- Facilitating Value	0.738	0.738	0.651	0.801
FV2 <- Facilitating Value	0.838	0.837	0.792	0.877
FV3 <- Facilitating Value	0.848	0.848	0.807	0.881
FV4 <- Facilitating Value	0.755	0.753	0.679	0.818
PE1 <- Performance Expectancy	0.878	0.878	0.839	0.909
PE2 <- Performance Expectancy	0.899	0.899	0.856	0.930

Table A.14 continued

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
PE3 <- Performance Expectancy	0.935	0.935	0.916	0.949
PE4 <- Performance Expectancy	0.862	0.861	0.814	0.899
PE5 <- Performance Expectancy	0.867	0.868	0.821	0.907
T1 <- Trust	0.895	0.894	0.867	0.916
T2 <- Trust	0.889	0.888	0.856	0.913
T3 <- Trust	0.641	0.641	0.545	0.727
T4 <- Trust	0.761	0.761	0.694	0.812
T5 <- Trust	0.850	0.850	0.806	0.887

Table A.15

Confidence Intervals Bias Corrected (Outer Loadings)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
DL1 <- Digital Literacy	0.717	0.718	0.001	0.638	0.779
DL2 <- Digital Literacy	0.842	0.840	-0.002	0.792	0.875
DL3 <- Digital Literacy	0.842	0.840	-0.001	0.808	0.872
DL4 <- Digital Literacy	0.777	0.778	0.001	0.717	0.822
DL5 <- Digital Literacy	0.579	0.581	0.001	0.469	0.661
DSCI1 <- Digital Supply Chain Intention	0.826	0.825	-0.001	0.761	0.872
DSCI2 <- Digital Supply Chain Intention	0.601	0.601	0.000	0.485	0.680
DSCI3 <- Digital Supply Chain Intention	0.817	0.816	-0.001	0.762	0.866
DSCI4 <- Digital Supply Chain Intention	0.851	0.851	0.001	0.812	0.882

Table A.15 continued

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
DSCI5 <- Digital Supply Chain Intention	0.791	0.791	0.000	0.697	0.854
DSCP1 <- Digital Supply Chain Practice	0.912	0.911	0.000	0.872	0.937
DSCP2 <- Digital Supply Chain Practice	0.942	0.942	-0.001	0.920	0.960
DSCP3 <- Digital Supply Chain Practice	0.944	0.944	0.000	0.924	0.958
DSCP4 <- Digital Supply Chain Practice	0.917	0.916	0.000	0.873	0.946
DSCP5 <- Digital Supply Chain Practice	0.916	0.915	-0.001	0.881	0.942
FC1 <- Facilitating Condition	0.750	0.750	0.000	0.671	0.818
FC2 <- Facilitating Condition	0.776	0.775	-0.001	0.697	0.828
FC3 <- Facilitating Condition	0.834	0.835	0.001	0.771	0.880
FC4 <- Facilitating Condition	0.842	0.841	0.000	0.790	0.882
FC5 <- Facilitating Condition	0.807	0.807	0.000	0.759	0.844
FV1 <- Facilitating Value	0.738	0.738	0.000	0.643	0.797
FV2 <- Facilitating Value	0.838	0.837	-0.001	0.791	0.877
FV3 <- Facilitating Value	0.848	0.848	0.001	0.800	0.877
FV4 <- Facilitating Value	0.755	0.753	-0.001	0.680	0.821
PE1 <- Performance Expectancy	0.878	0.878	0.000	0.838	0.909
PE2 <- Performance Expectancy	0.899	0.899	-0.001	0.853	0.928
PE3 <- Performance Expectancy	0.935	0.935	0.000	0.916	0.949
PE4 <- Performance Expectancy	0.862	0.861	-0.001	0.813	0.899
PE5 <- Performance Expectancy	0.867	0.868	0.001	0.810	0.901
T1 <- Trust	0.895	0.894	-0.001	0.867	0.916
T2 <- Trust	0.889	0.888	0.000	0.855	0.912

Table A.15 continued

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
T3 <- Trust	0.641	0.641	0.000	0.540	0.722
T4 <- Trust	0.761	0.761	0.000	0.693	0.811
T5 <- Trust	0.850	0.850	0.000	0.802	0.882

Table A.16

Outer Weights predictive items on the constructs (Mean, STDEV, t-Values, p-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
DL1 <- Digital Literacy	0.198	0.198	0.025	7.853	0.000
DL2 <- Digital Literacy	0.298	0.297	0.021	14.464	0.000
DL3 <- Digital Literacy	0.320	0.318	0.023	13.764	0.000
DL4 <- Digital Literacy	0.248	0.249	0.023	10.735	0.000
DL5 <- Digital Literacy	0.251	0.251	0.033	7.704	0.000
DSCI1 <- Digital Supply Chain Intention	0.286	0.286	0.016	17.870	0.000
DSCI2 <- Digital Supply Chain Intention	0.180	0.180	0.019	9.596	0.000
DSCI3 <- Digital Supply Chain Intention	0.247	0.248	0.015	16.547	0.000
DSCI4 <- Digital Supply Chain Intention	0.317	0.316	0.017	19.165	0.000
DSCI5 <- Digital Supply Chain Intention	0.232	0.232	0.017	13.407	0.000
DSCP1 <- Digital Supply Chain Practice	0.223	0.223	0.008	29.758	0.000

Table A.16 continued

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
DSCP2 <- Digital Supply Chain Practice	0.215	0.215	0.006	34.326	0.000
DSCP3 <- Digital Supply Chain Practice	0.220	0.220	0.006	35.835	0.000
DSCP4 <- Digital Supply Chain Practice	0.212	0.212	0.007	29.464	0.000
DSCP5 <- Digital Supply Chain Practice	0.209	0.210	0.008	26.500	0.000
FC1 <- Facilitating Condition	0.193	0.194	0.021	9.105	0.000
FC2 <- Facilitating Condition	0.268	0.267	0.023	11.614	0.000
FC3 <- Facilitating Condition	0.253	0.254	0.018	13.968	0.000
FC4 <- Facilitating Condition	0.270	0.269	0.019	14.119	0.000
FC5 <- Facilitating Condition	0.259	0.258	0.020	12.809	0.000
FV1 <- Facilitating Value	0.278	0.279	0.024	11.642	0.000
FV2 <- Facilitating Value	0.315	0.313	0.020	15.809	0.000
FV3 <- Facilitating Value	0.365	0.366	0.023	15.751	0.000
FV4 <- Facilitating Value	0.294	0.293	0.021	14.196	0.000
PE1 <- Performance Expectancy	0.216	0.217	0.010	22.219	0.000
PE2 <- Performance Expectancy	0.220	0.220	0.011	20.624	0.000
PE3 <- Performance Expectancy	0.240	0.239	0.007	34.438	0.000
PE4 <- Performance Expectancy	0.219	0.219	0.009	23.691	0.000
PE5 <- Performance Expectancy	0.230	0.231	0.010	24.196	0.000
T1 <- Trust	0.272	0.271	0.013	20.407	0.000

Table A.16 continued

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
T2 <- Trust	0.273	0.272	0.014	19.334	0.000
T3 <- Trust	0.176	0.175	0.018	9.968	0.000
T4 <- Trust	0.222	0.222	0.015	14.627	0.000
T5 <- Trust	0.274	0.275	0.015	18.442	0.000

Table A.17

Confidence Intervals (Outer Weights)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
DL1 <- Digital Literacy	0.198	0.198	0.148	0.242
DL2 <- Digital Literacy	0.298	0.297	0.257	0.340
DL3 <- Digital Literacy	0.320	0.318	0.277	0.368
DL4 <- Digital Literacy	0.248	0.249	0.206	0.293
DL5 <- Digital Literacy	0.251	0.251	0.188	0.317
DSCI1 <- Digital Supply Chain Intention	0.286	0.286	0.254	0.317
DSCI2 <- Digital Supply Chain Intention	0.180	0.180	0.143	0.217
DSCI3 <- Digital Supply Chain Intention	0.247	0.248	0.221	0.276
DSCI4 <- Digital Supply Chain Intention	0.317	0.316	0.285	0.354
DSCI5 <- Digital Supply Chain Intention	0.232	0.232	0.196	0.264
DSCP1 <- Digital Supply Chain Practice	0.223	0.223	0.208	0.238
DSCP2 <- Digital Supply Chain Practice	0.215	0.215	0.203	0.228
DSCP3 <- Digital Supply Chain Practice	0.220	0.220	0.209	0.233
DSCP4 <- Digital Supply Chain Practice	0.212	0.212	0.197	0.225
DSCP5 <- Digital Supply Chain Practice	0.209	0.210	0.195	0.227
FC1 <- Facilitating Condition	0.193	0.194	0.154	0.235
FC2 <- Facilitating Condition	0.268	0.267	0.225	0.314

Table A.17 continued

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
FC3 <- Facilitating Condition	0.253	0.254	0.221	0.292
FC4 <- Facilitating Condition	0.270	0.269	0.235	0.310
FC5 <- Facilitating Condition	0.259	0.258	0.220	0.299
FV1 <- Facilitating Value	0.278	0.279	0.230	0.324
FV2 <- Facilitating Value	0.315	0.313	0.270	0.350
FV3 <- Facilitating Value	0.365	0.366	0.325	0.416
FV4 <- Facilitating Value	0.294	0.293	0.253	0.337
PE1 <- Performance Expectancy	0.216	0.217	0.197	0.237
PE2 <- Performance Expectancy	0.220	0.220	0.199	0.239
PE3 <- Performance Expectancy	0.240	0.239	0.227	0.253
PE4 <- Performance Expectancy	0.219	0.219	0.200	0.237
PE5 <- Performance Expectancy	0.230	0.231	0.211	0.250
T1 <- Trust	0.272	0.271	0.245	0.298
T2 <- Trust	0.273	0.272	0.248	0.302
T3 <- Trust	0.176	0.175	0.140	0.207
T4 <- Trust	0.222	0.222	0.193	0.253
T5 <- Trust	0.274	0.275	0.249	0.304

Table A.18

Confidence Intervals Bias Corrected (Outer weights)

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
DL1 <- Digital Literacy	0.198	0.198	0.001	0.137	0.239
DL2 <- Digital Literacy	0.298	0.297	-0.002	0.262	0.345
DL3 <- Digital Literacy	0.320	0.318	-0.002	0.283	0.377
DL4 <- Digital Literacy	0.248	0.249	0.001	0.205	0.291

Table A.18 continued

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
DL5 <- Digital Literacy	0.251	0.251	0.000	0.189	0.323
DSCI1 <- Digital Supply Chain Intention	0.286	0.286	0.000	0.257	0.321
DSCI2 <- Digital Supply Chain Intention	0.180	0.180	0.000	0.143	0.218
DSCI3 <- Digital Supply Chain Intention	0.247	0.248	0.001	0.220	0.274
DSCI4 <- Digital Supply Chain Intention	0.317	0.316	-0.001	0.292	0.357
DSCI5 <- Digital Supply Chain Intention	0.232	0.232	0.000	0.196	0.264
DSCP1 <- Digital Supply Chain Practice	0.223	0.223	0.000	0.208	0.238
DSCP2 <- Digital Supply Chain Practice	0.215	0.215	0.000	0.203	0.228
DSCP3 <- Digital Supply Chain Practice	0.220	0.220	0.000	0.209	0.233
DSCP4 <- Digital Supply Chain Practice	0.212	0.212	0.000	0.198	0.226
DSCP5 <- Digital Supply Chain Practice	0.209	0.210	0.001	0.195	0.227
FC1 <- Facilitating Condition	0.193	0.194	0.001	0.153	0.234
FC2 <- Facilitating Condition	0.268	0.267	-0.001	0.226	0.320
FC3 <- Facilitating Condition	0.253	0.254	0.001	0.217	0.291
FC4 <- Facilitating Condition	0.270	0.269	-0.001	0.236	0.314
FC5 <- Facilitating Condition	0.259	0.258	-0.001	0.223	0.306
FV1 <- Facilitating Value	0.278	0.279	0.002	0.226	0.317
FV2 <- Facilitating Value	0.315	0.313	-0.002	0.278	0.360
FV3 <- Facilitating Value	0.365	0.366	0.001	0.325	0.416
FV4 <- Facilitating Value	0.294	0.293	-0.001	0.257	0.338
PE1 <- Performance Expectancy	0.216	0.217	0.000	0.196	0.236
PE2 <- Performance Expectancy	0.220	0.220	0.000	0.199	0.239
PE3 <- Performance Expectancy	0.240	0.239	0.000	0.228	0.256
PE4 <- Performance Expectancy	0.219	0.219	-0.001	0.202	0.242
PE5 <- Performance Expectancy	0.230	0.231	0.001	0.211	0.250
T1 <- Trust	0.272	0.271	-0.001	0.246	0.298
T2 <- Trust	0.273	0.272	0.000	0.249	0.305
T3 <- Trust	0.176	0.175	0.000	0.139	0.206
T4 <- Trust	0.222	0.222	0.000	0.193	0.253
T5 <- Trust	0.274	0.275	0.001	0.248	0.304

Table A.19

Inner Model

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facilitating Condition	Facilitating Value	Performance Expectancy	Trust
Digital Literacy		1.000					
Digital Supply Chain Intention			1.000				
Facilitating Condition		1.000					
Facilitating Value		1.000					
Performance Expectancy		1.000					
Trust		1.000					

Table A.20

Outer Model

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facilitating Condition	Facilitating Value	Performance Expectancy	Trust
DL1	-1.000						
DL2	-1.000						
DL3	-1.000						
DL4	-1.000						
DL5	-1.000						
DSCI1		-1.000					
DSCI2		-1.000					

Table A.20 continued

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facilitating Condition	Facilitating Value	Performance Expectancy	Trust
DSCI3		-1.000					
DSCI4		-1.000					
DSCI5		-1.000					
DSCP1			-1.000				
DSCP2			-1.000				
DSCP3			-1.000				
DSCP4			-1.000				
DSCP5			-1.000				
FC1				-1.000			
FC2				-1.000			
FC3				-1.000			
FC4				-1.000			
FC5				-1.000			
FV1					-1.000		
FV2					-1.000		
FV3					-1.000		
FV4					-1.000		
PE1						-1.000	
PE2						-1.000	
PE3						-1.000	
PE4						-1.000	
PE5						-1.000	
T1							-1.000
T2							-1.000
T3							-1.000
T4							-1.000
T5							-1.000

Table A.21

MV Descriptives

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
DL1	67.795	71.000		100.000	25.010	-0.047	-0.651	434.000
DL2	75.576	80.000		100.000	23.172	0.411	-0.926	434.000
DL3	74.931	80.000		100.000	23.480	0.245	-0.901	434.000
DL4	73.675	80.000		100.000	25.198	0.322	-0.965	434.000
DL5	68.265	73.000		100.000	27.531	-0.321	-0.698	434.000
DSCI1	78.675	82.000		100.000	20.840	1.628	-1.171	434.000
DSCI2	64.935	70.000		100.000	30.401	-0.539	-0.704	434.000
DSCI3	72.719	77.000		100.000	24.053	0.792	-0.994	434.000
DSCI4	76.666	81.000		100.000	23.259	1.272	-1.176	434.000
DSCI5	76.965	80.000		100.000	22.023	1.215	-1.079	434.000
DSCP1	74.629	80.000		100.000	26.538	0.955	-1.187	434.000
DSCP2	74.094	80.000		100.000	26.422	1.091	-1.225	434.000
DSCP3	74.447	81.000		100.000	26.708	0.986	-1.221	434.000
DSCP4	74.106	81.000		100.000	26.321	1.242	-1.283	434.000
DSCP5	75.118	81.000		100.000	25.845	1.453	-1.314	434.000
FC1	73.401	80.000		100.000	25.510	0.085	-0.885	434.000
FC2	82.048	90.000		100.000	22.551	1.652	-1.425	434.000
FC3	73.406	77.000		100.000	24.234	0.563	-0.937	434.000
FC4	75.113	82.000		100.000	25.617	0.579	-1.078	434.000
FC5	73.217	79.000		100.000	26.352	0.122	-0.922	434.000
FV2	71.435	76.000		100.000	24.293	-0.074	-0.736	434.000
FV3	70.806	74.000		100.000	22.909	0.010	-0.691	434.000
FV4	66.896	70.000		100.000	25.481	-0.300	-0.615	434.000
PE1	73.788	78.000		100.000	23.470	0.908	-1.013	434.000
PE2	76.419	80.000		100.000	22.676	0.911	-1.076	434.000
PE3	76.650	82.000		100.000	23.433	1.384	-1.217	434.000
PE4	72.548	77.000		100.000	23.825	1.046	-1.070	434.000
PE5	76.553	80.000		100.000	22.847	1.505	-1.216	434.000
T1	76.166	81.000		100.000	23.584	0.698	-1.066	434.000

Table A.21 continued

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
T2	74.433	80.000		100.000	24.135	0.547	-0.994	434.000
T3	71.318	77.000		100.000	27.776	-0.178	-0.859	434.000
T4	67.998	73.000		100.000	26.383	-0.058	-0.748	434.000
T5	73.415	76.000		100.000	23.361	0.957	-0.998	434.000
FV1	68.293	70.000		100.000	24.495	-0.328	-0.546	434.000

Table A.21

Latent Variable Correlations

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facili-tating Condition	Facili-tating Value	Perfor-mance Expectancy	Trust
Digital Literacy	1.000	0.507	0.375	0.554	0.505	0.578	0.589
Digital Supply Chain Intention	0.507	1.000	0.659	0.555	0.548	0.727	0.674
Digital Supply Chain Practice	0.375	0.659	1.000	0.473	0.461	0.699	0.620
Facilitating Condition	0.554	0.555	0.473	1.000	0.552	0.606	0.663
Facilitating Value	0.505	0.548	0.461	0.552	1.000	0.560	0.640
Performance Expectancy	0.578	0.727	0.699	0.606	0.560	1.000	0.791

Table A.21 continued

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facili-tating Condition	Facili-tating Value	Perfor-mance Expectancy	Trust
Trust	0.589	0.674	0.620	0.663	0.640	0.791	1.000

Table A.22

Latent Variable Covariances

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facili-tating Condition	Facili-tating Value	Perfor-mance Expectancy	Trust
Digital Literacy	1.000	0.507	0.375	0.554	0.505	0.578	0.589
Digital Supply Chain Intention	0.507	1.000	0.659	0.555	0.548	0.727	0.674
Digital Supply Chain Practice	0.375	0.659	1.000	0.473	0.461	0.699	0.620
Facilitating Condition	0.554	0.555	0.473	1.000	0.552	0.606	0.663
Facilitating Value	0.505	0.548	0.461	0.552	1.000	0.560	0.640
Performance Expectancy	0.578	0.727	0.699	0.606	0.560	1.000	0.791
Trust	0.589	0.674	0.620	0.663	0.640	0.791	1.000

Table A.23

LV Descriptives

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skew-ness	Number of Observations Used
Digital Literacy	0.000	0.170	-3.474	1.459	1.000	0.486	-0.743	434.000
Digital Supply Chain Intention	0.000	0.064	-4.069	1.342	1.000	1.315	-0.928	434.000
Digital Supply Chain Practice	0.000	0.217	-3.049	1.045	1.000	1.784	-1.368	434.000
Facilitating Condition	0.000	0.167	-3.808	1.218	1.000	0.642	-0.921	434.000
Facilitating Value	0.000	0.110	-3.600	1.577	1.000	0.510	-0.641	434.000
Performance Expectancy	0.000	0.155	-3.642	1.197	1.000	1.090	-1.035	434.000
Trust	0.000	0.148	-3.603	1.326	1.000	1.119	-0.993	434.000

Table A.24

Outer Model Residual Descriptives

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
DL1	0.000	0.141	-2.654	1.799	0.697	1.865	-0.868	434.000
DL2	0.000	-0.032	-2.689	2.098	0.540	2.790	-0.358	434.000
DL3	0.000	-0.046	-2.547	1.808	0.540	2.371	-0.221	434.000

Table A.24 continued

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
DL4	0.000	0.018	-2.755	2.584	0.630	3.809	-0.708	434.000
DL5	0.000	0.172	-2.796	2.357	0.815	2.009	-1.019	434.000
DSCI1	0.000	-0.085	-1.862	3.250	0.564	4.924	0.873	434.000
DSCI2	0.000	0.321	-2.587	1.432	0.799	1.954	-1.558	434.000
DSCI3	0.000	0.047	-3.150	1.477	0.577	6.944	-1.858	434.000
DSCI4	0.000	-0.010	-2.954	2.071	0.526	6.333	-0.898	434.000
DSCI5	0.000	-0.016	-3.530	3.431	0.612	8.365	-0.182	434.000
DSCP1	0.000	0.004	-2.864	1.737	0.411	8.772	-0.871	434.000
DSCP2	0.000	-0.004	-2.110	1.788	0.334	8.854	-0.557	434.000
DSCP3	0.000	-0.011	-1.783	1.229	0.330	5.791	-0.903	434.000
DSCP4	0.000	0.026	-3.036	2.237	0.400	14.308	-1.703	434.000
DSCP5	0.000	0.005	-2.666	1.764	0.401	8.661	-0.710	434.000
FC1	0.000	0.090	-3.224	3.049	0.661	5.232	-0.966	434.000
FC2	0.000	-0.101	-2.970	2.586	0.631	3.077	0.415	434.000
FC3	0.000	0.082	-3.174	2.113	0.552	7.800	-1.609	434.000
FC4	0.000	-0.003	-2.869	1.504	0.540	7.162	-1.588	434.000
FC5	0.000	0.049	-2.525	1.662	0.590	2.338	-0.866	434.000
FV1	0.000	0.041	-2.673	3.094	0.675	2.777	-0.231	434.000
FV2	0.000	-0.041	-2.205	2.334	0.545	2.268	0.241	434.000
FV3	0.000	-0.043	-2.971	1.702	0.531	2.785	-0.268	434.000
FV4	0.000	0.109	-2.945	2.246	0.656	4.389	-1.448	434.000
PE1	0.000	0.064	-2.366	1.970	0.479	6.090	-0.960	434.000
PE2	0.000	-0.037	-1.825	2.992	0.437	8.198	0.528	434.000
PE3	0.000	-0.036	-1.665	1.687	0.354	5.084	-0.055	434.000
PE4	0.000	0.120	-3.080	2.633	0.507	9.897	-1.675	434.000
PE5	0.000	-0.012	-3.516	2.579	0.498	10.895	-0.585	434.000
T1	0.000	-0.033	-1.620	2.009	0.446	2.015	0.284	434.000

Table A.24 continued

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
T2	0.000	-0.007	-2.093	1.489	0.459	3.815	-0.856	434.000
T3	0.000	0.154	-2.853	2.938	0.767	2.849	-1.049	434.000
T4	0.000	0.195	-2.726	1.563	0.649	3.361	-1.491	434.000
T5	0.000	0.011	-3.220	1.705	0.528	6.499	-1.035	434.000

Table A.25

Inner Model Residual Correlation

	Digital Supply Chain Intention	Digital Supply Chain Practice
Digital Supply Chain Intention	1.000	-0.308
Digital Supply Chain Practice	-0.308	1.000

Table A.26

Inner Model Residual Descriptives

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observa-tions Used
Digital Supply Chain Intention	0.000	0.009	-2.890	3.056	0.653	3.956	0.088	434.000
Digital Supply Chain Practice	0.000	0.135	-3.614	2.302	0.752	6.841	-1.993	434.000

Table A.27

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Digital Literacy	0.809	0.827	0.869	0.574
Digital Supply Chain Intention	0.839	0.865	0.886	0.612
Digital Supply Chain Practice	0.959	0.959	0.968	0.858
Facilitating Condition	0.862	0.868	0.900	0.644
Facilitating Value	0.807	0.818	0.873	0.634
Performance Expectancy	0.933	0.935	0.949	0.790
Trust	0.868	0.890	0.906	0.660

Table 4.28

Discriminant Validity (Cross Loadings)

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facili-tating Condition	Facili-tating Value	Perfor-mance Expectancy	Trust
DL1	0.717	0.283	0.229	0.337	0.306	0.349	0.345
DL2	0.842	0.426	0.319	0.478	0.406	0.483	0.489
DL3	0.842	0.457	0.323	0.497	0.455	0.489	0.517
DL4	0.777	0.354	0.231	0.417	0.396	0.436	0.431
DL5	0.579	0.359	0.293	0.329	0.318	0.399	0.410
DSCI1	0.445	0.826	0.527	0.521	0.491	0.670	0.620
DSCI2	0.226	0.601	0.394	0.243	0.298	0.366	0.359
DSCI3	0.385	0.817	0.506	0.380	0.405	0.537	0.507
DSCI4	0.452	0.851	0.661	0.501	0.497	0.690	0.611
DSCI5	0.436	0.791	0.443	0.471	0.414	0.508	0.488
DSCP1	0.360	0.632	0.912	0.440	0.457	0.627	0.573
DSCP2	0.348	0.608	0.942	0.440	0.436	0.669	0.582
DSCP3	0.331	0.622	0.944	0.414	0.408	0.663	0.550

Table 4.28 continued

	Digital Literacy	Digital Supply Chain Intention	Digital Supply Chain Practice	Facili-tating Condition	Facili-tating Value	Perfor-mance Expectancy	Trust
DSCP4	0.357	0.598	0.917	0.458	0.408	0.637	0.600
DSCP5	0.340	0.591	0.916	0.442	0.427	0.644	0.565
FC1	0.434	0.342	0.318	0.750	0.473	0.372	0.479
FC2	0.418	0.475	0.366	0.776	0.371	0.462	0.421
FC3	0.483	0.448	0.386	0.834	0.438	0.494	0.551
FC4	0.473	0.479	0.410	0.842	0.482	0.541	0.584
FC5	0.419	0.459	0.407	0.807	0.464	0.538	0.622
FV1	0.338	0.384	0.374	0.380	0.738	0.405	0.487
FV2	0.406	0.435	0.379	0.492	0.838	0.467	0.551
FV3	0.472	0.506	0.400	0.469	0.848	0.511	0.536
FV4	0.378	0.407	0.313	0.408	0.755	0.388	0.461
PE1	0.543	0.621	0.591	0.558	0.504	0.878	0.743
PE2	0.499	0.630	0.598	0.531	0.498	0.899	0.688
PE3	0.542	0.687	0.646	0.554	0.495	0.935	0.718
PE4	0.453	0.629	0.640	0.478	0.480	0.862	0.666
PE5	0.529	0.660	0.629	0.570	0.511	0.867	0.701
T1	0.557	0.604	0.532	0.615	0.601	0.700	0.895
T2	0.510	0.606	0.557	0.605	0.571	0.708	0.889
T3	0.433	0.390	0.369	0.408	0.402	0.447	0.641
T4	0.381	0.494	0.480	0.450	0.437	0.542	0.761
T5	0.505	0.608	0.553	0.582	0.560	0.762	0.850

Table 4.29

Collinearity Statistics (VIF)

	VIF
DL1	1.689
DL2	2.190
DL3	2.057
DL4	1.716
DL5	1.187
DSCI1	2.026
DSCI2	1.419
DSCI3	2.109
DSCI4	2.132
DSCI5	1.907
DSCP1	4.024
DSCP2	6.045
DSCP3	6.052
DSCP4	4.282
DSCP5	4.190
FC1	1.717
FC2	1.699
FC3	2.125
FC4	2.145
FC5	1.987
FV1	1.477
FV2	1.935
FV3	1.862
FV4	1.503
PE1	3.001
PE2	3.705
PE3	5.096
PE4	2.673
PE5	2.659

Table 4.29 continued

	VIF
T1	3.651
T2	3.547
T3	1.403
T4	1.716
T5	2.205

Table 4.30

Model_Fit

	Saturated Model	Estimated Model
SRMR	0.054	0.074
d_ULS	1.756	3.275
d_G	0.666	0.709
Chi-Square	1654.202	1726.139
NFI	0.856	0.850

Table 4.31

Model Selection Criteria

	AIC (Akaike's Information Criterion)	AICu (Unbiased Akaikes Information Criterion	AICc (Corrected Akaikes Information Criterion)	BIC (Bayesian Information Criteria)	HQ (Hannan Quinn Criterion)	HQc (Corrected Hannan-Quinn Criterion)
Digital Supply Chain Intention	-359.065	-353.023	77.198	-334.627	-349.419	-349.012
Digital Supply Chain Practice	-244.640	-242.636	191.416	-236.494	-241.425	-241.358

Figure A.1 Path Coefficients (DL -> DSCI)

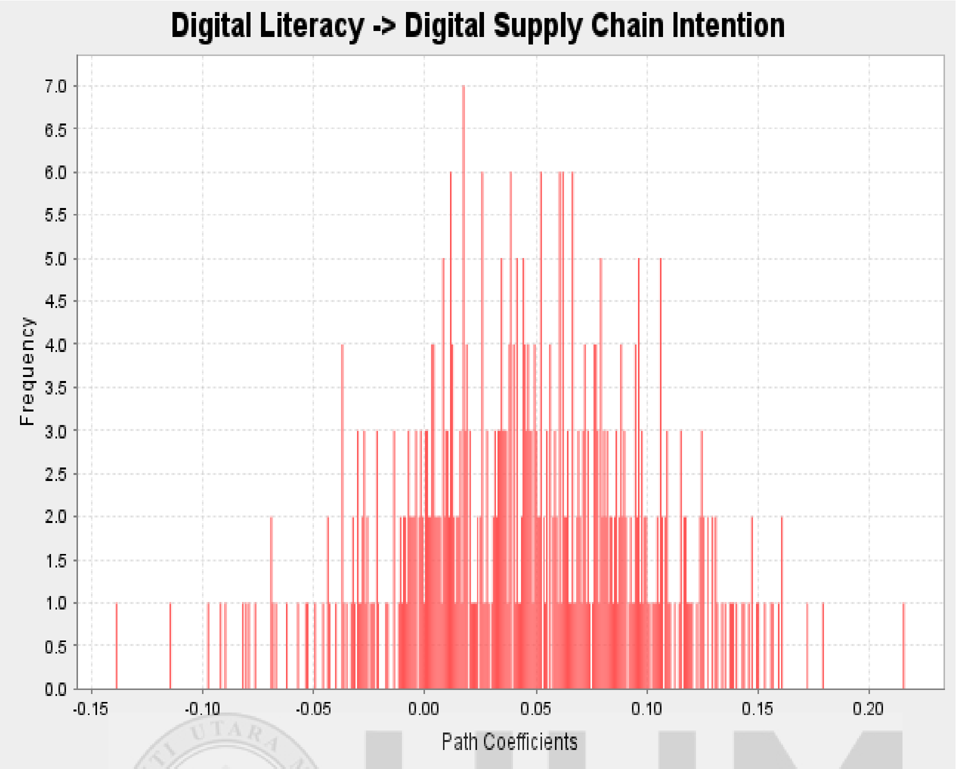


Figure A.2 Path Coefficients (DSCI -> DSCP)

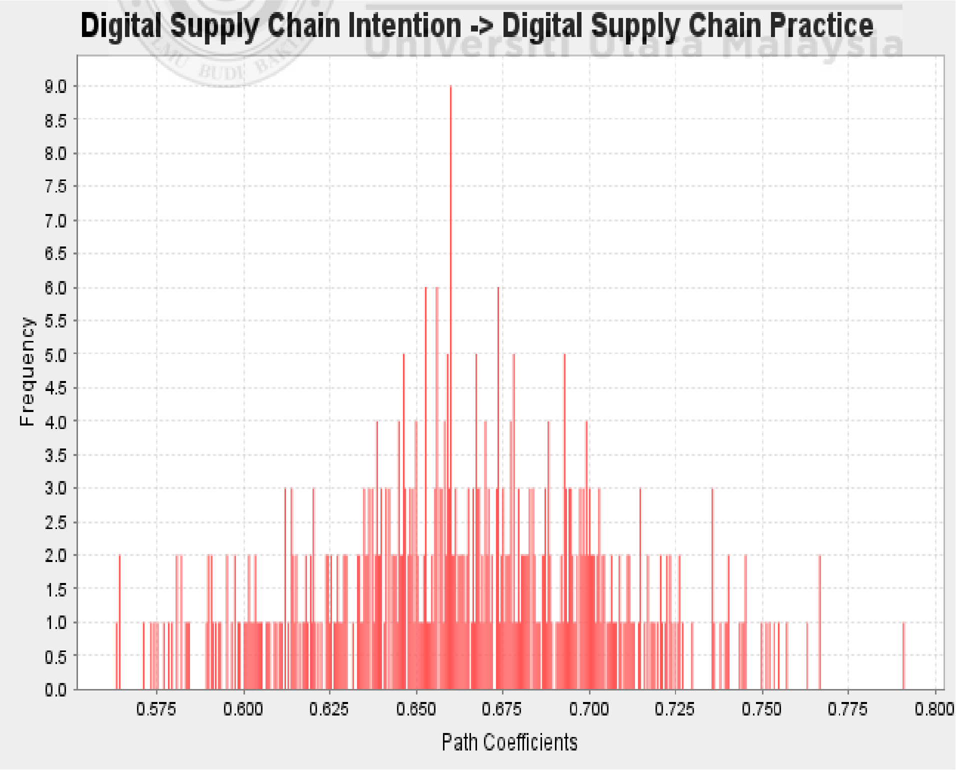


Figure A.3 Path Coefficients (FC -> DSCI)

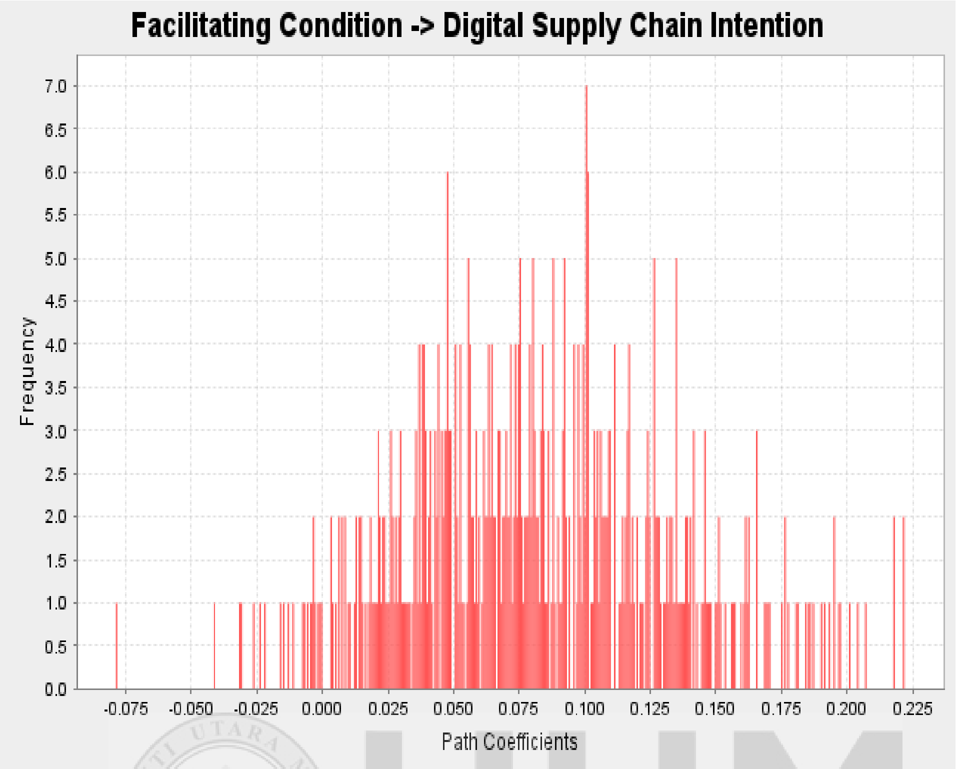


Figure A.4 Path Coefficients (FV -> DSCI)

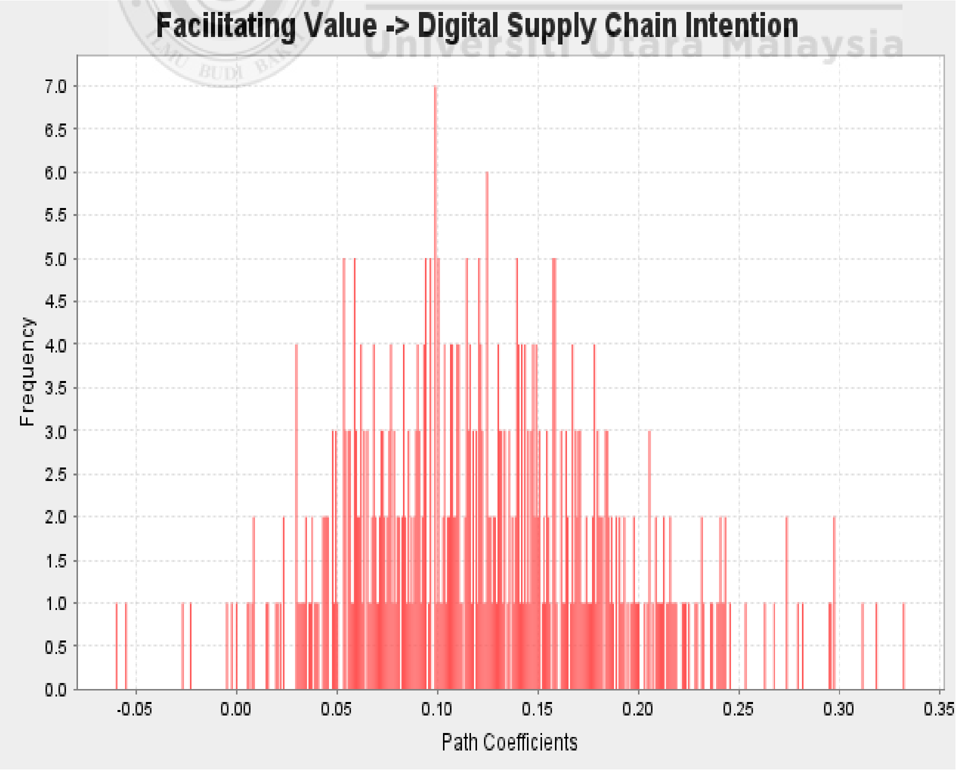


Figure A.5 Path Coefficients (PE -> DSCI)

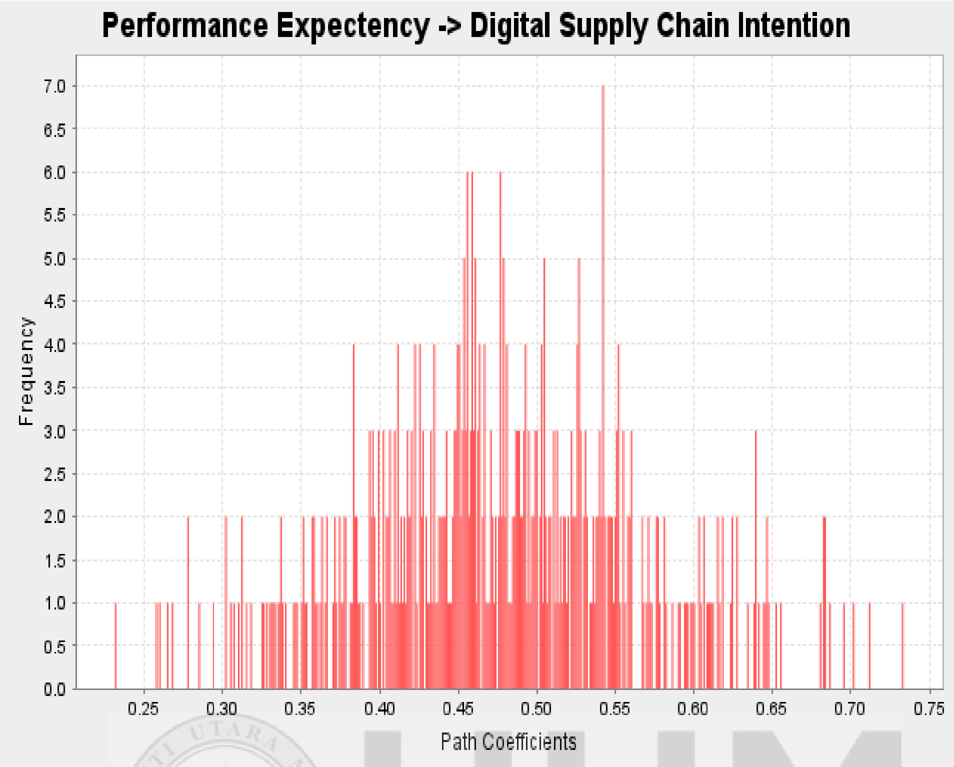


Figure A.6 Path Coefficients (T -> DSCI)

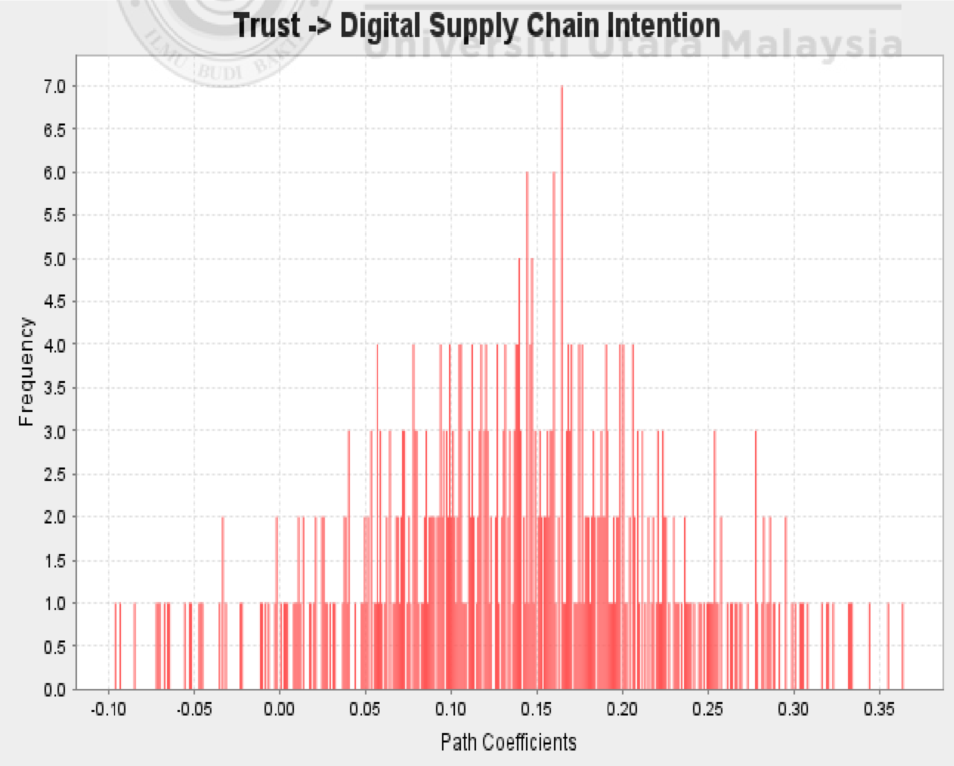


Figure A.7 Indirect Effects (DL -> DSCP)

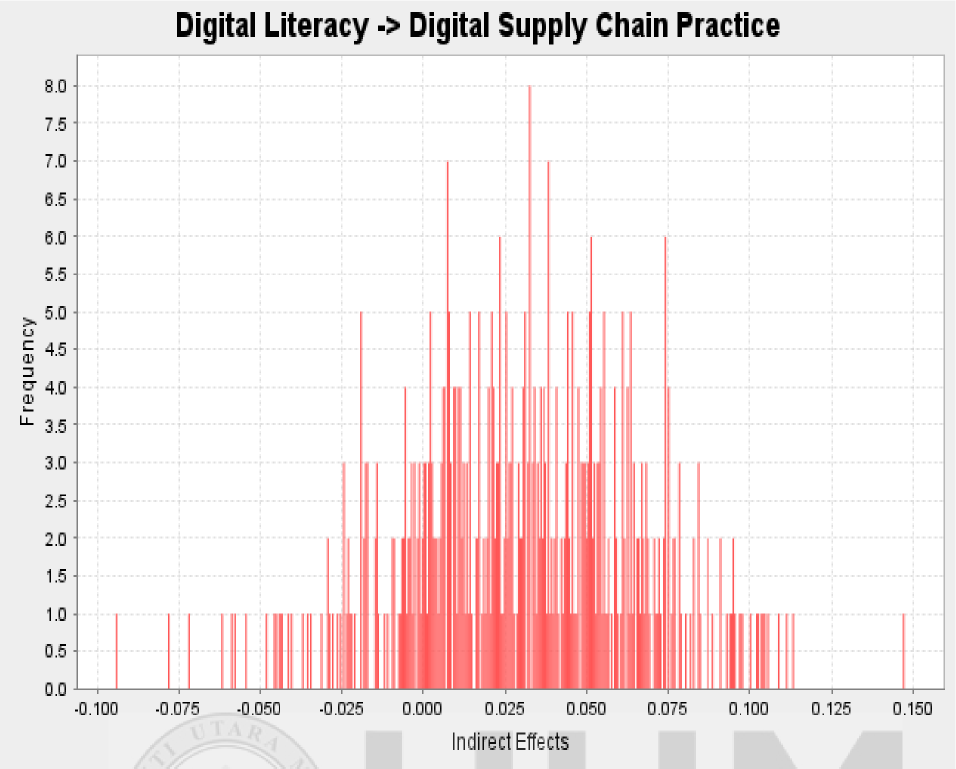


Figure A.8 Indirect Effects (FC -> DSCP)

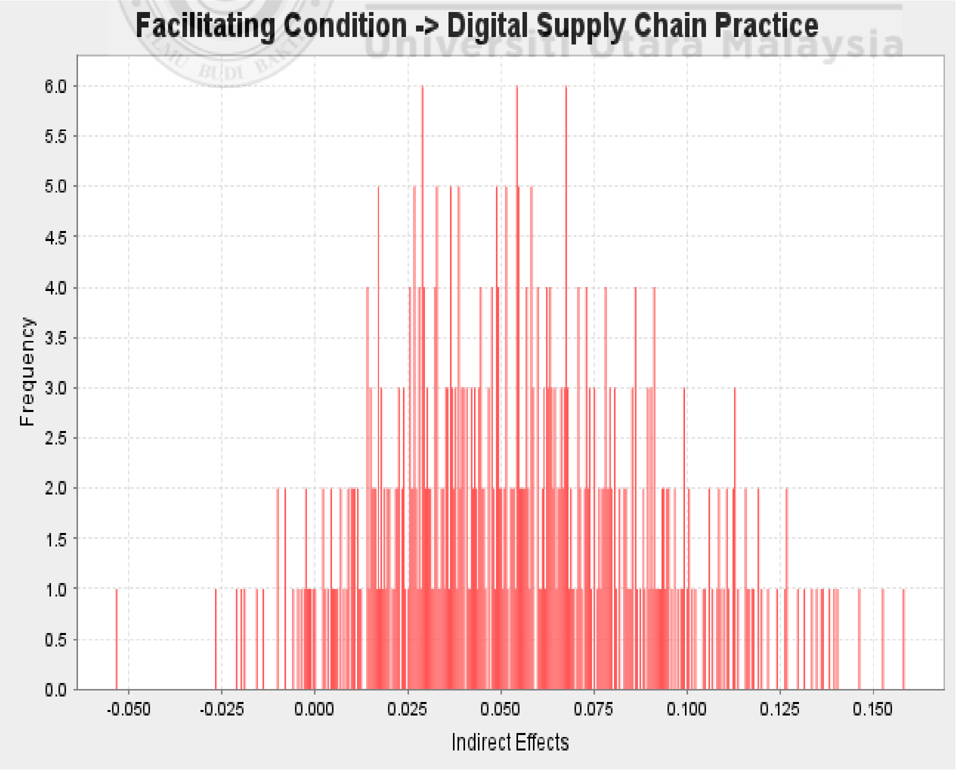


Figure A.9 Indirect Effects (FV -> DSCP)

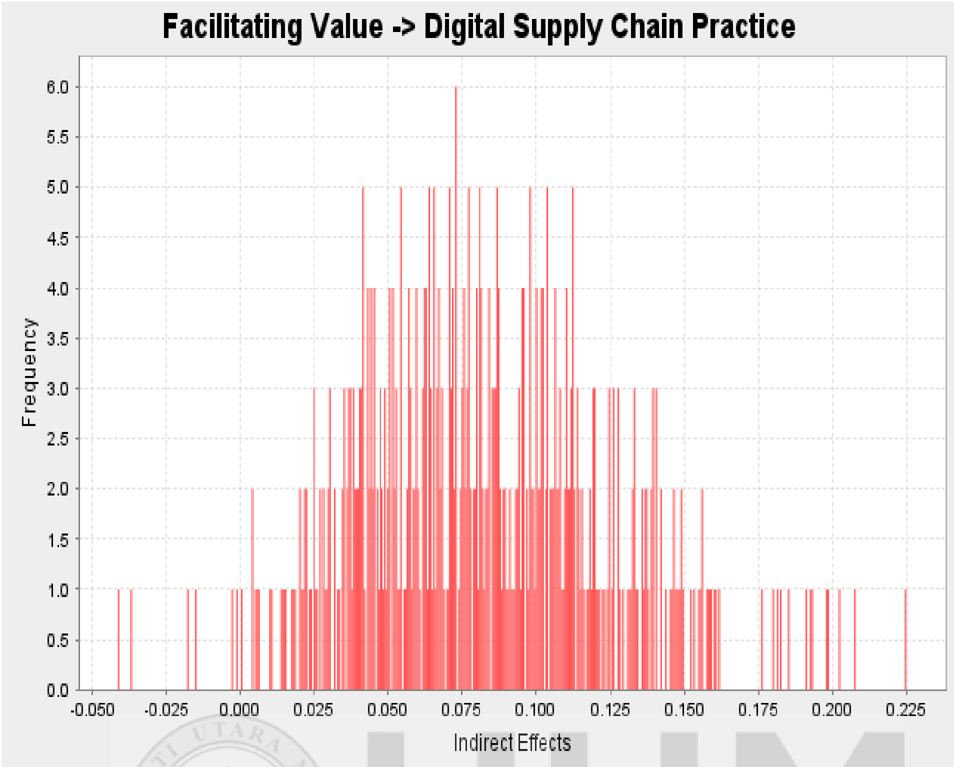


Figure A.10 Indirect Effects (PE -> DSCP)

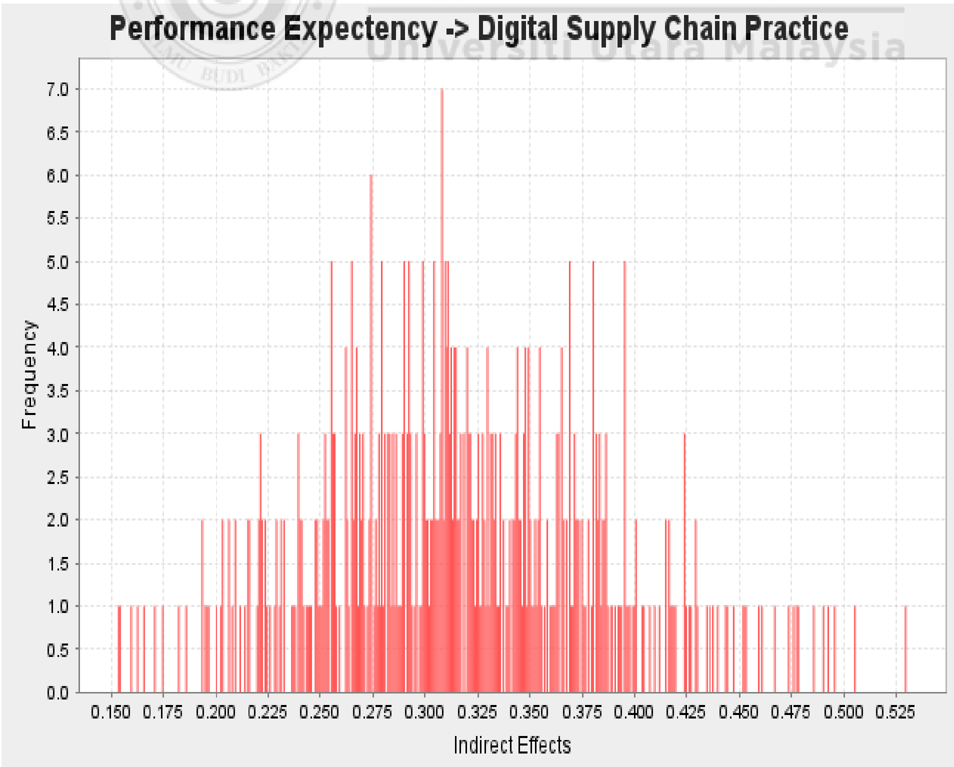


Figure A.11 Indirect Effects (T -> DSCP)

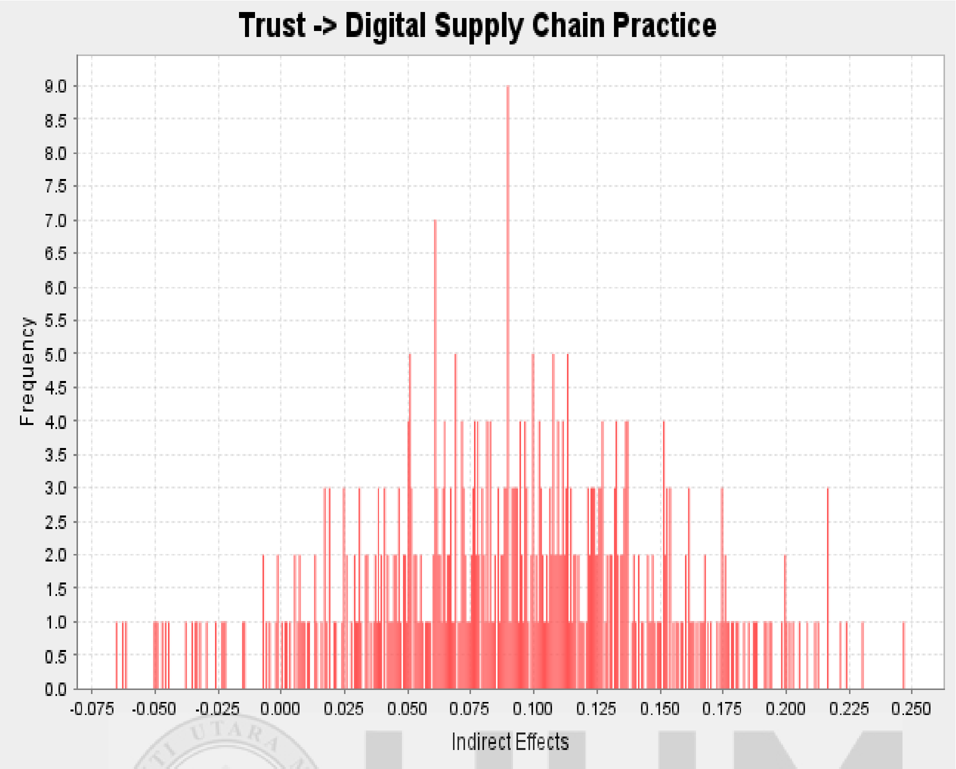


Figure A.12 Total Effects (DL -> DSCI)

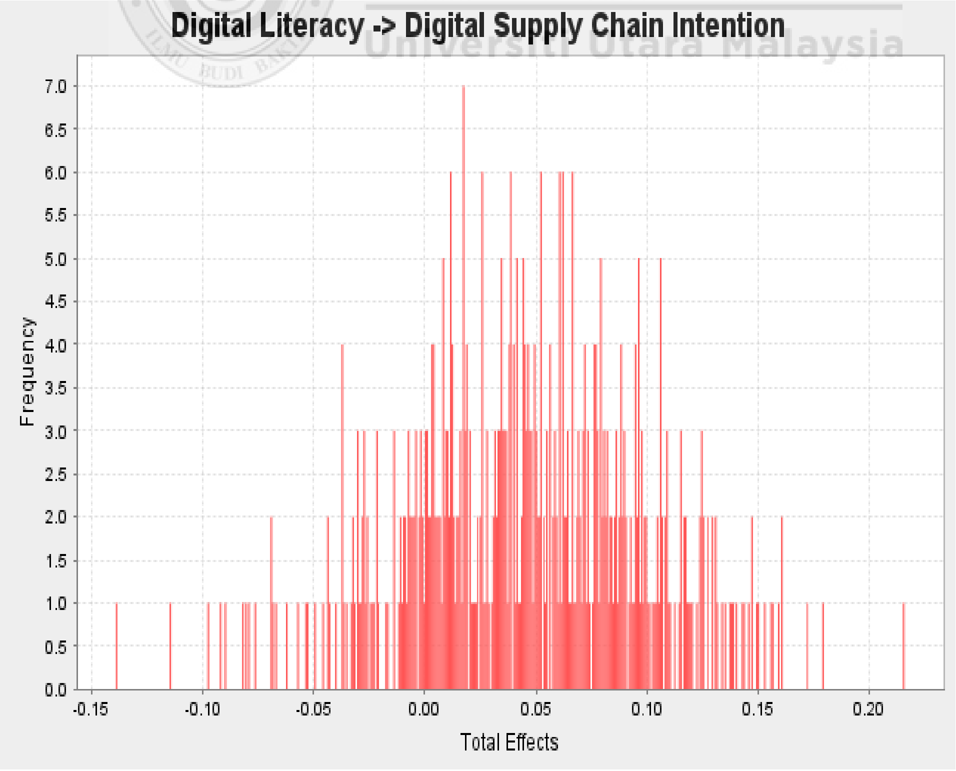


Figure A.13 Total Effects (DL -> DSCP)

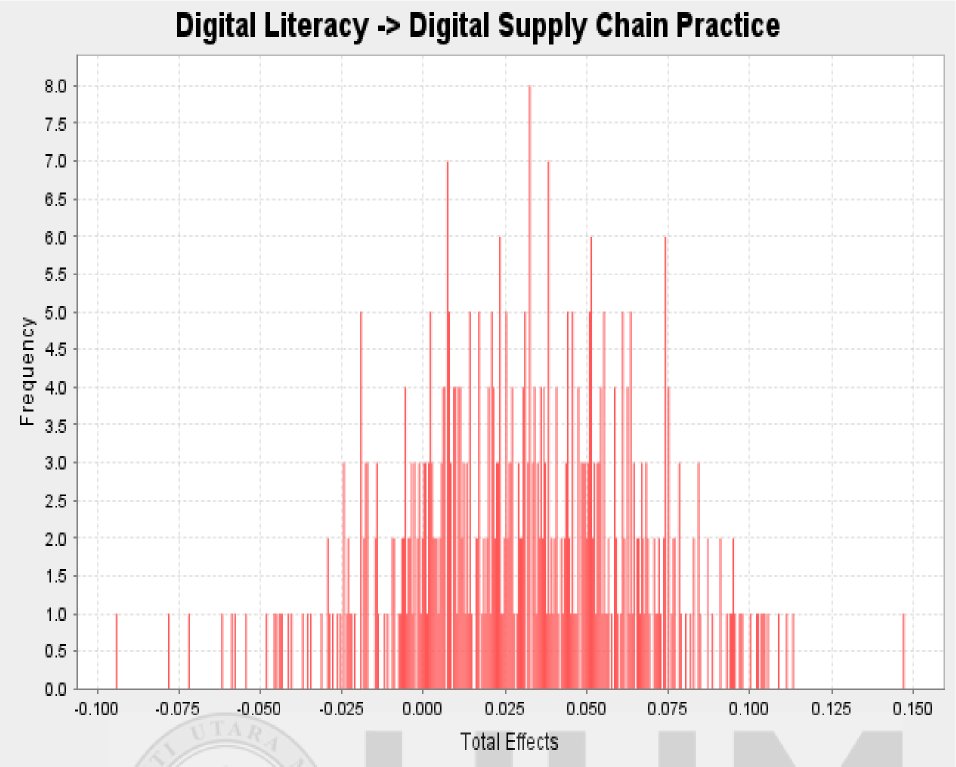


Figure A.14 Total Effects (DSCI -> DSCP)

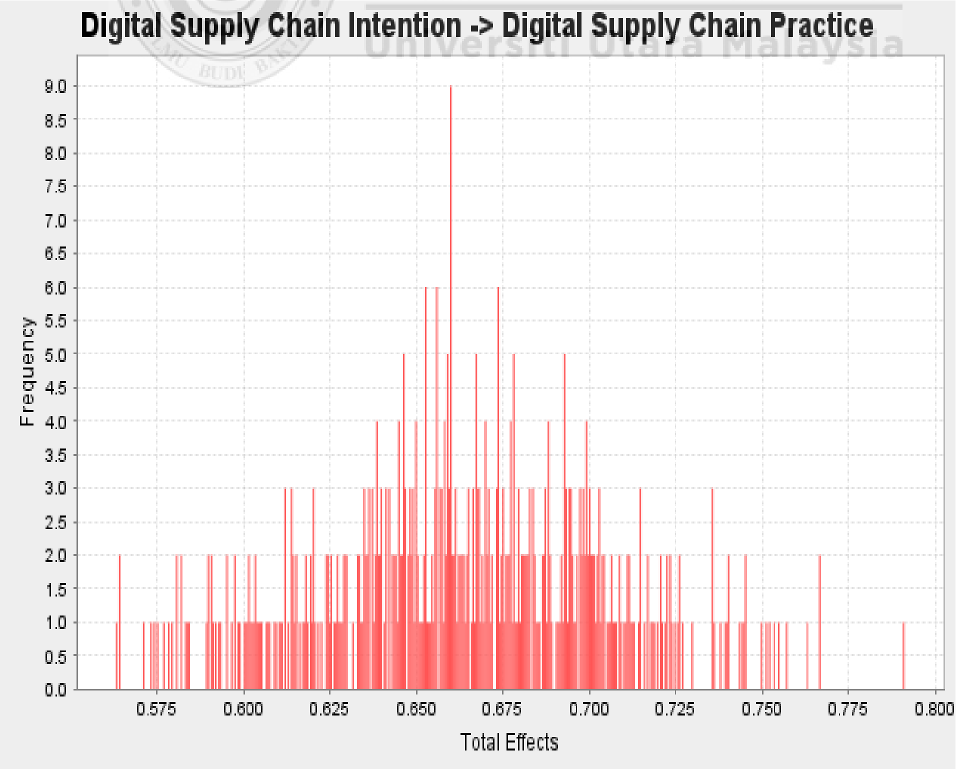


Figure A.15 Total Effects (FC -> DSCI)

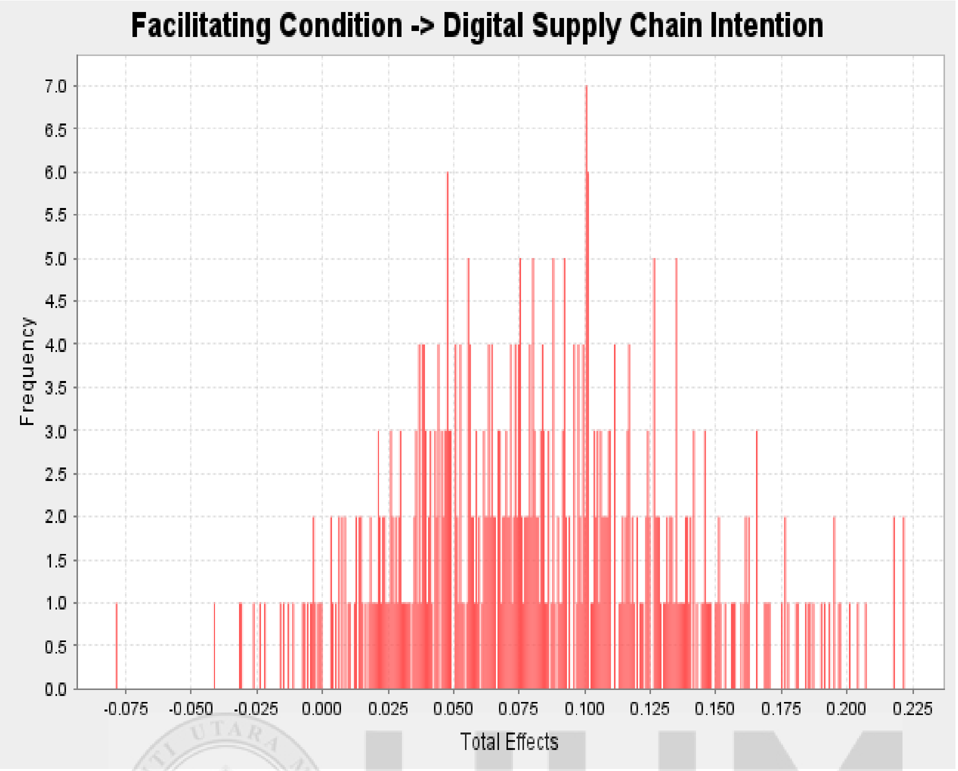


Figure A.16 Total Effects (FC -> DSCP)

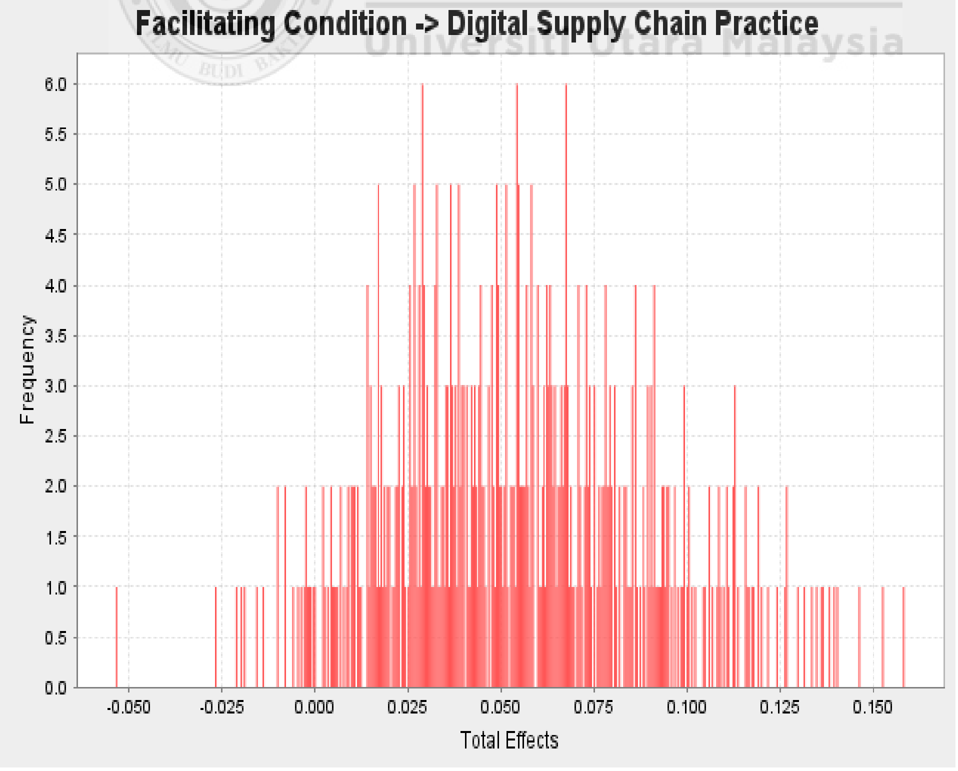


Figure A.17 Total Effects (FV -> DSCI)

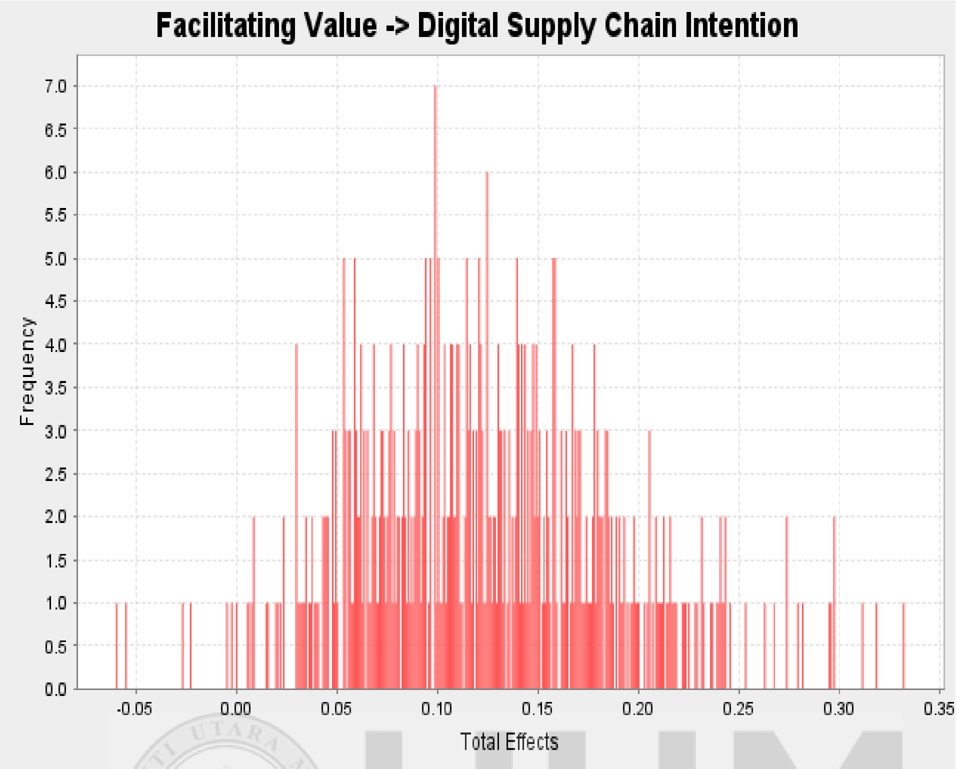


Figure A.18 Total Effects (FV -> DSCP)

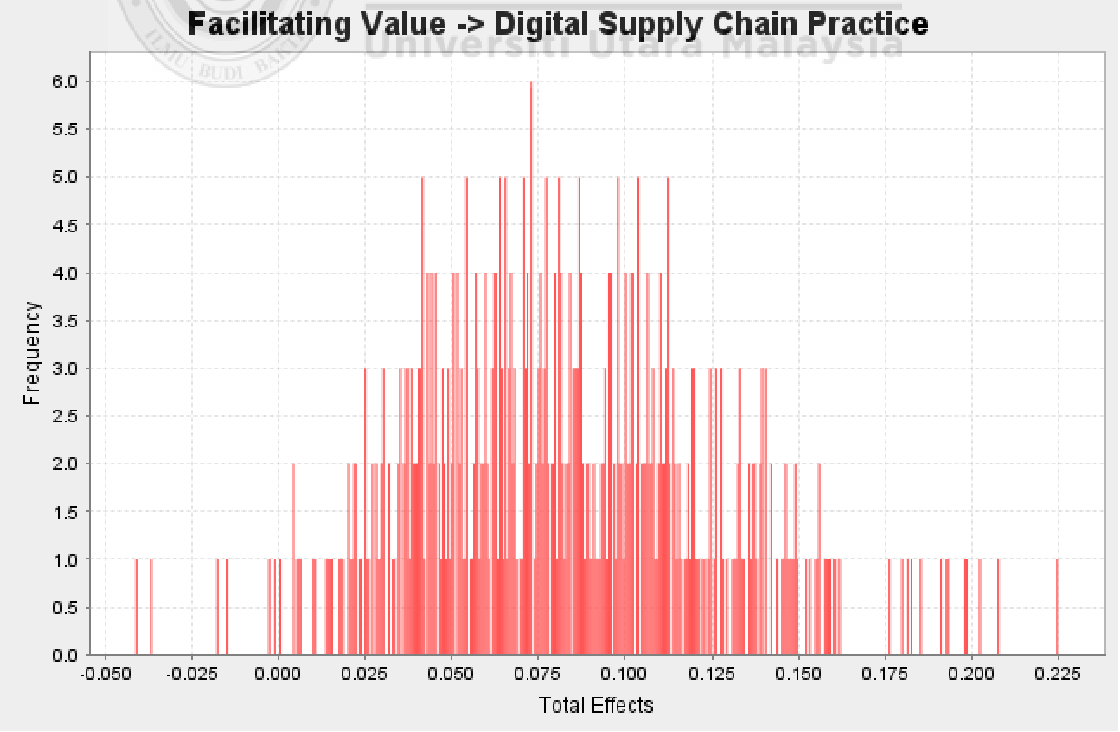


Figure A.19 Total Effects (PE -> DSCI)

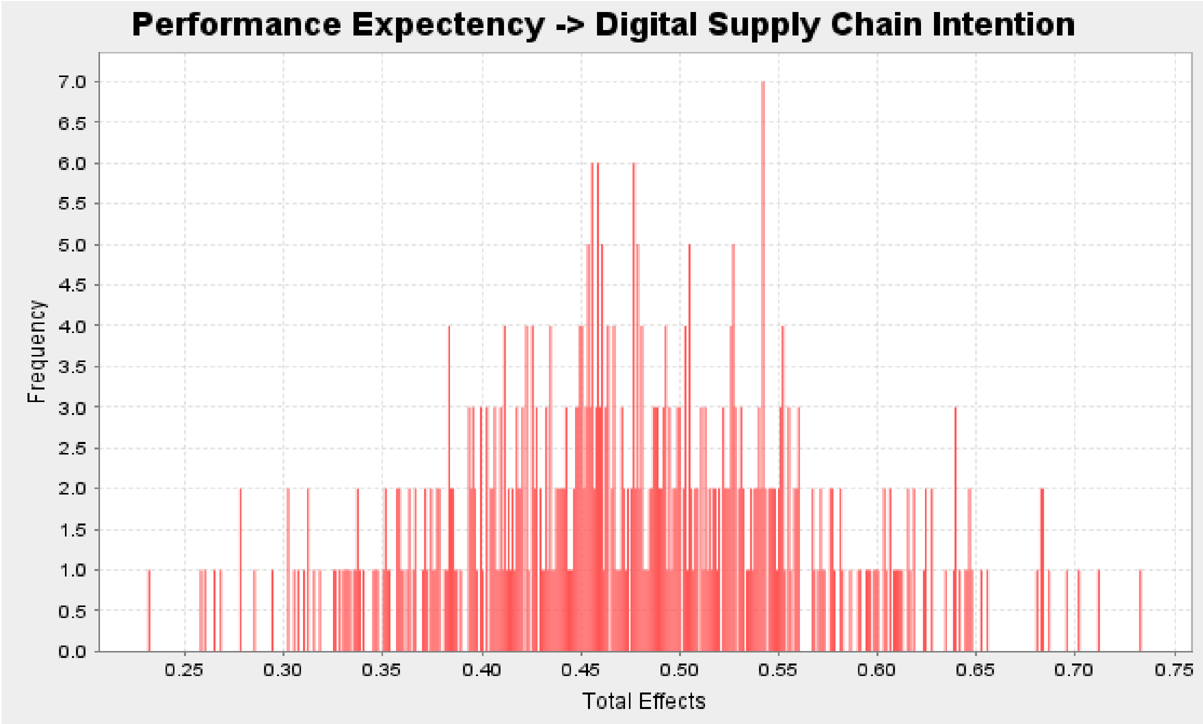


Figure A.20 Total Effects (PE -> DSCP)

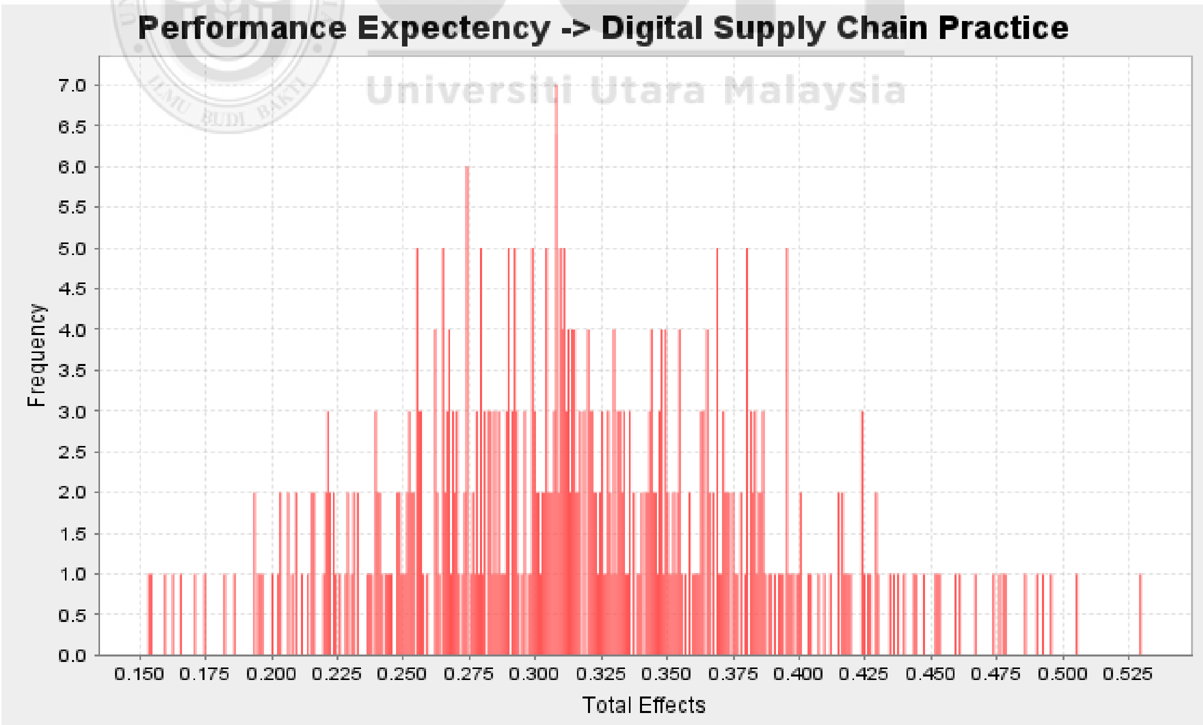


Figure A.21 Total Effects (T -> DSCI)

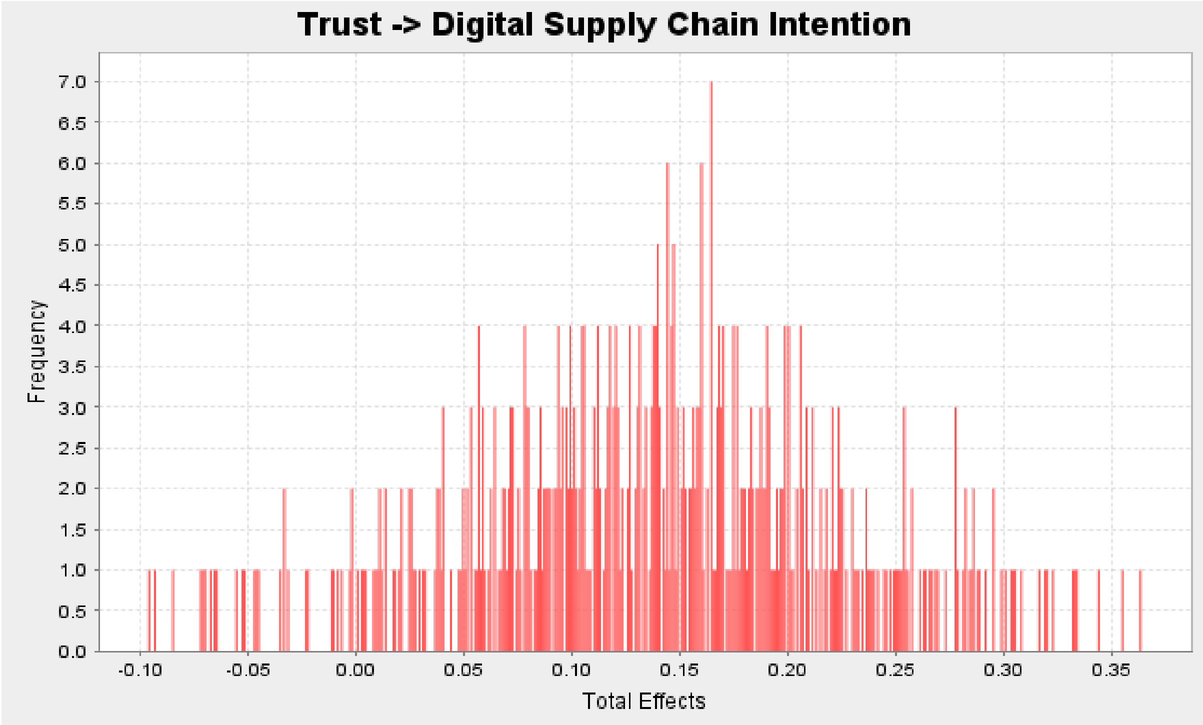
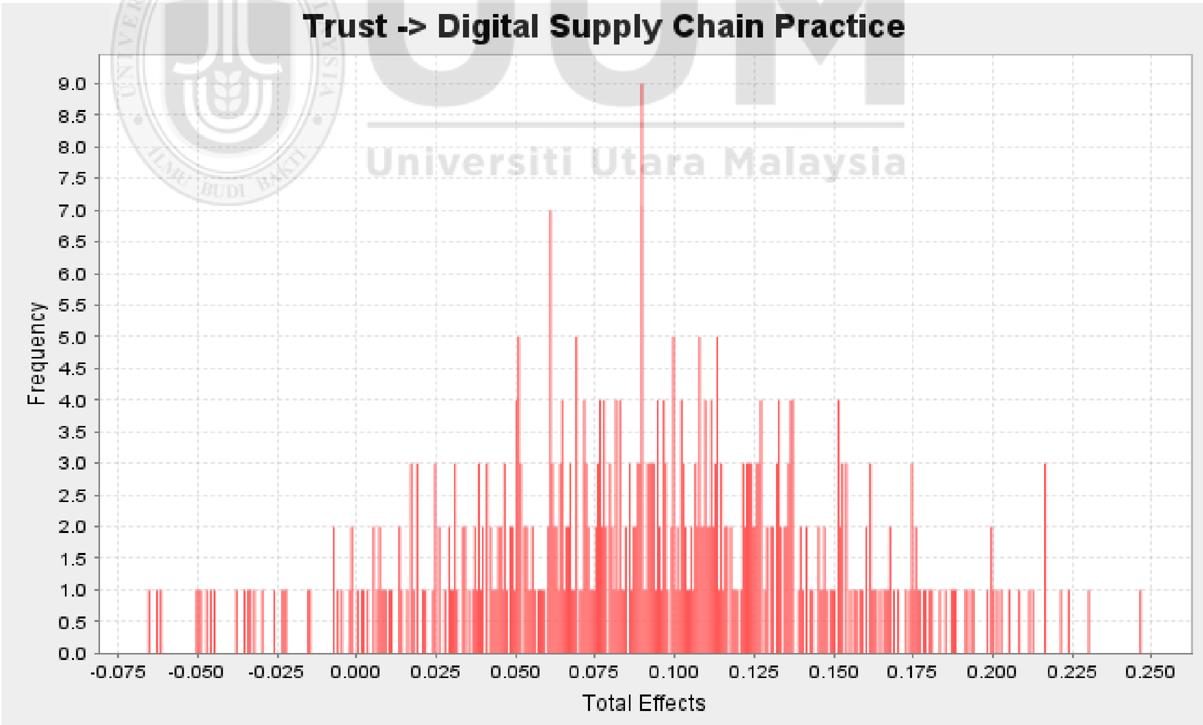


Figure A.22 Total Effects (T -> DSCP)



APPENDIX B. QUESTIONNAIRE

School of Quantitative Science,
Universiti Utara Malaysia

Dear Respondents,

I am a PhD student of Universiti Utara Malaysia (UUM). I am conducting a study on "**FACTORS THAT INFLUENCE DIGITAL SUPPLY CHAIN PRACTICES MEDIATED BY STAKEHOLDERS' INTENTION IN HIGHER EDUCATION INSTITUTES OF THE LEAST DEVELOPED COUNTRIES".**

I would appreciate it very much if you could answer the questions carefully as the information you provide will influence the accuracy and the success of this research. It will take no longer than 5 minutes to complete the questionnaire. All answers will be treated with strict confidence and will be used for the purpose of the study only.

If you have any questions regarding this research, you may contact me at the following address. **manzur@aiub.edu**.

Thank you for your cooperation and the time taken in answering this questionnaire.

Your Sincerely,
S A M Manzur Hossain Khan
Universiti Utara Malaysia
Sintok, Kedah.

Section 1: (Demographic Profile): Please use tick mark (√) for each statement below.

1. Gender:

Male ☐ Female ☐

2. Age:

19-25 ☐ 26-35 ☐ 36-45 ☐ 46 & Above ☐

3. Highest Academic Level:

Diploma ☐ Bachelor ☐ Master ☐ PhD ☐ Other Study ☐

4. Marital Status:

Single ☐ Married ☐

5. Occupation (at university):

Student ☐ Teacher ☐ Administrator ☐

6. Income, please indicate your/family's approximate monthly income (in US Dollar):

<= $ 600 ☐ $ 601- $1000 ☐ $1001 - $1500 ☐

$ 1501 $ - $ 2000 ☐ > $ 2000 ☐

7. State your current location

Urban ☐ Suburban ☐ Rural ☐

Section 2: Please place the slider from 0 to 100 for each statement below based on the scale. (0: not applicable or never have experienced; 1 – 100: the degree of your agreement with the statement (1: strongly disagree; 100: strongly agree)

Note: A Digital Supply Chain (DSC) is a customer-centric platform model that captures and maximizes utilization of real-time data coming from a variety of sources. It enables demand simulation, matching, sensing and management to optimize performance and minimize risks. The Digital Supply Chain is not about whether the goods or services are digital or physical. It refers to the way that the supply chain process is managed.

All the answers given in the following sections are needed to study factors that can represent the Digital Supply Chain general practice for a higher education institution in the least developed countries. For a better understanding, the definition of each attribute studied in this research is provided in each section.

A) Facilitating Value

Definition: Academia perspective between perceived benefits and the monetary cost of using digital tools, networking and infrastructure in their Universities *to improve the service/information flows* <u>in a higher education institution supply chain.</u>

	Description	**0**	**1**				**100**
1	Digital tools, networking and ICT infrastructure in my University are reasonably priced.						
2	At the current price, digital tools, networking and ICT infrastructure in my University provides excellent value.						
3	Digital Supply Chain is capable to provide a better facility with a minimum cost incurring to the users in my University						
4	The value of Digital Supply Chain in my University worth its price.						

B) Facilitating Condition

***Definition**:* The degree to which academia believes the existence of digital tools, networking and infrastructure provided by their universities to *improve the service/information flows* <u>in a higher education institution supply chain.</u>

	Description	**0**	**1**				**100**
1	I have the necessary resources to use digital platform in my university						
2	I have the necessary knowledge to use digital platform in my university						
3	Digital tools, networking and ICT infrastructure in my University is compatible with other personal technologies I use.						

4	I can get help from others when I have difficulties using digital tools, networking and ICT infrastructure in my University							
5	My University always update or change its digital tools, networking and ICT infrastructure with the latest version.							

C) Digital Literacy

***Definition**:* The ability to use information and communication technologies to find, understand, evaluate, create, and communicate digital information *to improve the service/information flows* <u>in a higher education institution supply chain.</u>

	Description	**0**	**1**					**100**
1	I know how to solve my own ICT related technical problem							
2	I can learn new digital technologies easily							
3	I have the technical skill I need to use digital tools, networking and ICT infrastructure in my University for working (e.g.: online teaching-learning) that demonstrate my understanding of what I have learnt							
4	I am familiar with issues related to web-based activities (e.g.: plagiarism, cyber safety)							
5	I frequently obtain help with tasks from my friends over the Internet (e.g., through Facebook, Skype, Blogs)							

D) Trust

***Definition**: The level of belief with the reliability of* digital tools, networking and infrastructure in the DSC *to improve the service/information flows* <u>in a higher education institution supply chain.</u>

	Description	**0**	**1**					**100**
1	I trust the implementation of Digital Supply Chain in my University.							

2	I feel assured that legal and technological structures are implemented adequately in my University to protect me from problems in Digital Supply Chain practices							
3	I have doubt on the truthfulness of Digital Supply Chain in my university.							
4	Even if not monitored, I would trust the implementation of Digital Supply Chain practice to do the job correctly in my university							
5	The Digital Supply Chain can fulfill my required tasks relevant to University management.							

E) Performance Expectancy

***Definition**: The degree to which implementing the digital supply chain can improve the service/information flows in <u>a traditional higher education institution supply chain.</u>*

	Description	**0**	**1**					**100**
1	Digital Supply Chain increases the completion of the work tasks that are important to me.							
2	Digital Supply Chain helps me accomplish work tasks more quickly.							
3	Digital Supply Chain increases my work productivity.							
4.	Digital Supply Chain information received from other parties to complete my work tasks is always fast, accurate and informative.							
5.	I find Digital Supply Chain useful to enhance my University's performance.							

F) DSC Stakeholders Intention

***Definition**: The intention to practice digital supply chain to improve the service/information flows in <u>a traditional higher education institution supply chain</u>.*

	Description	**0**	**1**					**100**
1	I believe the Digital Supply Chain need proper user intention							

2	Academic supply chain performance does not need proper technology attraction							
3	User manual for digital supply chain practice is needed in my University to increase the productivity of academic supply chain							
4	I will continue practicing the digital supply chain for my work purpose in the future							
5	Organization’s stakeholders need proper adaptability on technology adoption							

G) Digital Supply Chain Practice

Definition*: The necessity and the urgency of using digital supply chain to improve the service/information flows in <u>a traditional higher education institution supply chain</u>.*

	Description	**0**	**1**					**100**
1	I find Digital Supply Chain useful in my job.							
2	Digital Supply Chain enables me to accomplish my job tasks more quickly.							
3	Digital Supply Chain increases my job productivity.							
4	In my institution, Digital Supply Chain enables me to receive fast, accurate and informative instruction/information about my job.							
5	Digital Supply Chain increases my creativity skills in doing my job							

APPENDIX C. CONCEPTUAL FRAMEWORK

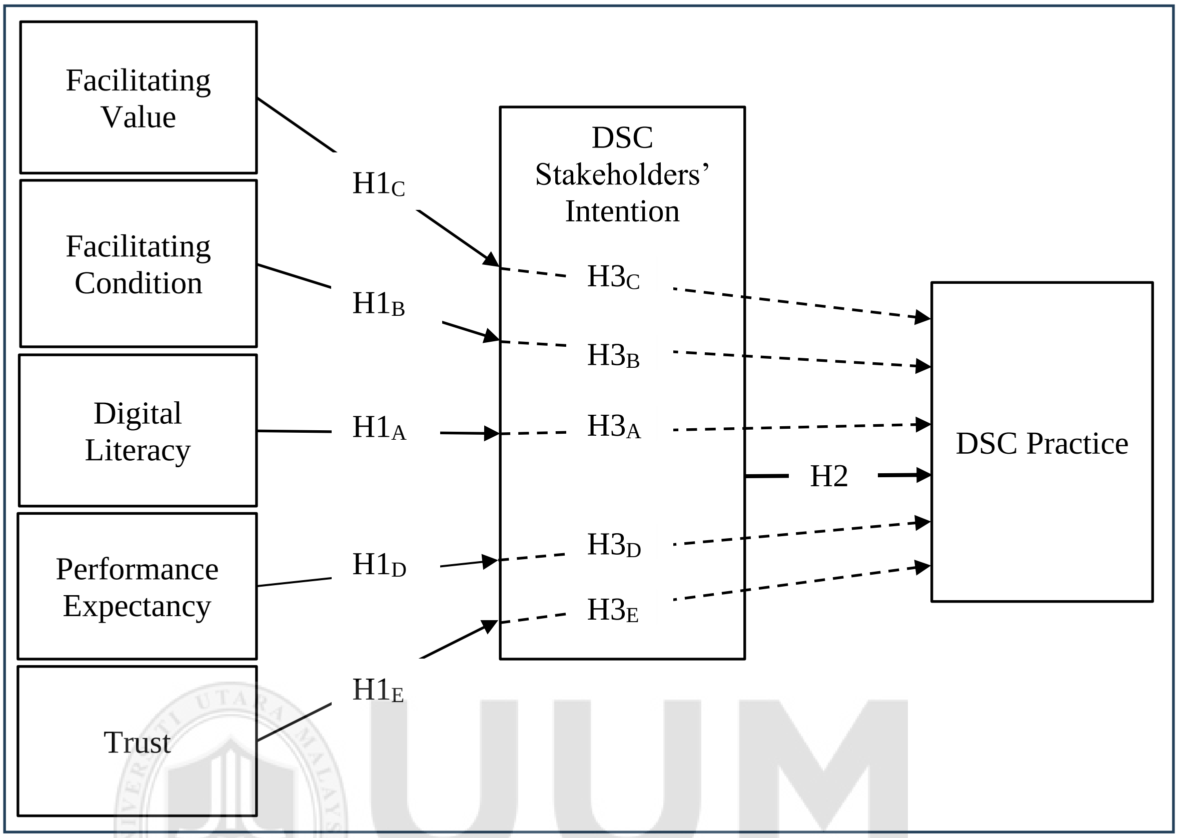


Figure C.1 Conceptual Framework of DSC Practice model for HEIs in LDCs