Unravelling the Web of E-Learning Adoption

Exploring the Impact of Network Effects on E-Learning Platform Adoption amongst University Students

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ABSTRACT

Since their advent, E-Learning platforms have been deemed resourceful and impactful tools for disseminating knowledge. They have been responsible for making education more vocational, accessible and interactive. Especially during the COVID-19 pandemic when the entire world was compelled to move online, e-Learning was a blessing in keeping education institutions up and running and the students engaged. However, the lack of adoption of e-Learning platforms still remains to be a challenge for platform makers and marketers. Therefore, it is significant to find innovative ways to drive the adoption of e-Learning platforms among students to explore the impact of network effects on the adoption of e-Learning platforms among university students. It also evaluates the role of two antecedents of trust – the propensity to trust and initial trust, in moderating the relationship between network effects and adoption intention. A quantitative method of research was employed and an experimental survey was circulated amongst university students in India, The Netherlands and The United States of America. The respondents were randomly assigned one out of the four conditions in the experiment, and 120 valid responses were collected. The data were analysed using hierarchical multiple regression analysis and Hayes' Moderation Analysis Model 2. The appropriate tests for reliability and validity were conducted. A manipulation check was conducted by forming the dummy correspondents for independent variables to check if the conditions were randomly assigned, along with a T-test. The results of the analysis were found to be insignificant for the impact of network effects on e-Learning adoption. Moreover, for moderation analysis, the interactions of moderating variables with dependent and independent variables were also found to be insignificant. The interpretation of the analysis was reported in the discussion chapter and the theoretical and practical implications of the study were traced. The research serves a pivotal foundation in the e-Learning adoption literature. The research model can be deployed to discern the factors affecting e-Learning adoption. This research also challenges and substantiates previous research on technology adoption. It concludes that platform heterogeneity, geographical factors, diversity in sample characteristics and cultural contexts should also be considered *while conducting research to understand the factors affecting e-Learning adoption amongst students.*

KEYWORDS: *Network Effects, Consumer Adoption, E-Learning, Trust.*

Contents

1. Introduction

The global online education market is anticipated to reach the revenue mark of US$57.42 billion in 2023 (Statista, n.d.), making it a lucrative arena to tap into. However, the blooming of the online education economy is still dependent on the adoption and acceptance of e-Learning technologies among students (Clay et al., 2008 as cited in Tarhini et al., 2014).

e-Learning technologies emerged in the 1990s to blend technical advances with education and learning (Brika et al., 2022). The technologies can be divided into many categories like subscribed content delivery, social network sites, virtual worlds, web blogs, e-Learning management systems, etc. (Craig et al., 2012). Nielson (2015) differentiates between the courses and platforms within the nexus of e-Learning. He suggests that courses designed by content providers, which are open to the public at large are called Massive Open Online Courses (MOOC). Whereas, the platforms on which these courses are provided are called Learning Management Systems. MOOC course content is usually provided or facilitated by Learning Management Systems, for instance, Coursera.

These platforms are a significant technological innovation, making learning more accessible. The content provided on the platforms has reportedly been of rich quality and boosts engagement among students, motivating them to interact with the course content (Rawashdeh et al., 2021). With the advent of the technological revolution and its rapid expansion across sectors, the process of learning has stepped out of the classroom, allowing access to profound avenues of knowledge, without impediments in the way of remote learning (Sudicky & Zounek, 2013). If the power of e-Learning platforms is harnessed efficiently and effectively, they can be useful in nourishing students' critical thinking skills, reducing costs for institutions and content providers, enhance the efficiency of educational institutions at large (Kimwise, 2017).

However, the adoption of e-Learning platforms still poses a challenge in the face of companies and educational institutions who create and curate content for these platforms. With the onset of the global pandemic caused by the COVID-19 outbreak, conventional educational infrastructure was impelled to move towards online systems of learning (Mathivanan et al., 2021). However, e-Learning, either mandated or recommended, could not reach its full adoption potential. Lack of awareness and skill set with Information and Communication Technology, lack of technological and financial infrastructure, resistance to change, etc., have been noted as some of the issues with the adoption of e-Learning technologies amongst consumers (Suleman et al., 2011; Majumdar et al., 2022).

Lastly and most importantly, low levels of adoption have also been identified as an issue fuelled by ineffective marketing strategies, making the potential of these platforms unfulfilled (Suleman et al., 2011). Kamba (2009) as cited by Mutsiya (2016) suggests that low levels of adoption have been recorded due to the lack and ineffectiveness of investment, commitment, and marketing efforts. This highlights the importance of devising innovative and effective marketing strategies to boost the adoption of e-Learning platforms. Hence, these findings from previous studies makes it pivotal for e-Learning platform providers to examine and explore innovative ways to drive the adoption of their products and services.

Reddy (2018) emphasizes the power of network effects in determining the success of any platform business. She also suggests that network effects can be effective in scaling up the business by accelerating the customer base, expanding market share and enhancing the value of the product, resulting in higher profits. In its essence, the notion of network effects entails the enhancement in the brand value of the product/service because of a higher user base (Stobeirski, 2020). The significance of network effects has been analysed in various cases within the product and service industry. Katona et al., (2011) in their study to assess the influence of network effects on prospective consumers of the online social network found a positive effect of current market share on prospective members. Their research suggests that a high market share can lead to higher adoption of online social networks among consumers. Similarly, Hsu (2016) provided empirical evidence that network externalities have a positive effect in driving the adoption of Internet of Things (IoT) services.

With regard to the adoption of e-Learning platforms, previous studies have identified factors like social influence (Nguyen et al., 2014), consumer attitude and the perceived value that they derive from the e-Learning technology (Liao et al., 2022), perceived computability, perceived trialability (Fu, 2007), etc. as having an influence on the adoption of e-Learning platforms. However, the influence of network effects, as used by companies to drive adoption, has not been empirically tested in the case of e-Learning platforms. An empirical investigation to understand the relationship between network effects and the adoption of e-Learning platforms would allow us to assess if network effects can be a key driver for adoption, helping platform owners to strategically market their e-Learning technologies by deploying network effects in their marketing and communication efforts.

Therefore, this project intends to answer the following research question:

RQ: “How do network effects impact the consumer adoption decision in the case of e-Learning technologies?”

This research aims to assess the role of network effects in driving the adoption of e-Learning platforms among consumers. The role of direct and indirect network effects will be evaluated in terms of their impact on consumer adoption intention. The research also considers trust as a variable and investigates its role as a moderator between network effects and the adoption intention of the consumer.

This study holds crucial relevance in terms of societal context and also has fruitful contributions to the current academic and scientific deliberation around e-Learning adoption.

1.1. Societal relevance

Firstly, e-Learning has opened up avenues for the education industry to function with more accessibility and touch way more lives than inside a conventional classroom. E-Learning technologies like Massive Open Online Courses (MOOCs) have the ability and potential to tap into the masses who don’t have equal access to education and other opportunities (De Moura et al., 2017). The research can be used to deploy network effects in marketing communication which can be beneficial in attracting people to adopt and access the rich content provided by various providers via e-Learning technologies and platforms. It would also enhance the brand image of the platform company which will not only make it attractive for potential customers but also lucrative for complimentary content providers, facilitating more variety and richer quality of content for the e-Learning platform. Increased adoption and a higher variety and quality of content providers can result in a boost in engagement, equipping students with more knowledge, expertise and necessary skills for the job market in the future. This could contribute to grooming high-performing, skilled and dexterous manpower, contributing to societal and economic growth.

Furthermore, Geith & Vignare (2008) suggested that there is a current gap in the demand and supply of education in the world. While emphasizing the significance of access to education and its lack, they propose focusing on online learning and its usage by academics to close the supply and demand gap in education. Additionally, they also discuss the importance of Open Education Courses provided by e-Learning platforms, and how a larger focus has to be on increasing accessibility of education to the masses. Using innovative techniques like harnessing the power of network effects could be used to drive adoption amongst students and could facilitate increased access to education by enhancing remote learning environments. This could be a crucial contribution to bridging the gap between the demand and supply of education. The increased adoption of e-Learning platforms facilitates a holistic and more efficient learning environment, increased accessibility to quality education, and a step towards achieving equality in education.

1.2. Scientific Relevance

Katona et al., (2011) suggest that understanding consumers through network effects can be used to deploy effective marketing strategies for the product/service. While network effects serve as a significant source to attract potential customers by tapping into the current customer network, they could also be used by larger firms to sustain their market power (Tucker, 2018). Moreover, they can also be crucial in making pricing decisions since the prospective customers' will to pay depends on the market share of the product/service (Stobierski, 2020).

Furthermore, it is imperative to address the issues students/consumers have with the adoption of e-Learning platforms, especially as a platform service provider or platform developer. This could provide a solution for issues like ineffective learning environments, lack of accessibility, etc. for both public and private educational institutions (Saleh et al., 2022). Another significant relevance of this study is that it facilitates an understanding of the key determinants which drive e-Learning adoption. While the study focuses on network effects as primary drivers, it also takes into account the role of antecedents of trust like propensity to trust and initial trust in the platform as moderators of this relationship between network effects and consumer adoption intention. Using the propensity to trust as a moderating variable helps investigate how personal characteristics and individual differences influence the adoption intention of the consumer (Mayer et al, 1989). And, using an Initial Trust moderator allows an examination of early-stage interactions between a consumer and technology, providing crucial insights into the trust-building characteristics of the consumer and its influence on their adoption intention (Kim & Prabhakar, 2004). Therefore, testing the role of these antecedents contributes to a detailed understanding of key drivers of consumer adoption behaviour with regard to consumer trust. This contributes significantly to the adoption literature for academics and could help platform makers and marketers to focus on trust-building mechanisms in their communication with the consumer. This model can also be deployed for further research in understanding these key drivers of adoption, which could also be used to assess adoption behaviour in the case of other technological innovations.

2. Theoretical Framework

This section provides a detailed conceptual overview of the notions and concepts used in this study. This overview synthesizes the extensive scholarly literature around the major concepts of the study. We embark on tracing the theoretical literature by understanding the nuances of technology acceptance. After which, the various conceptual definitions of E-Learning platforms will be laid out, as propounded by researchers in the past. The adoption intention will be elucidated within the ambit of e-commerce and e-Learning technologies. An overview of network effects literature will be traced to further understand the concept. Furthermore, a relationship between network effects and e-Learning adoption will be defined and hypothesized to substantiate the research model of this study. A deeper understanding of Trust and its antecedents would also be provided by tracing the literature on the concept, and its relevance will be established with the current study. Finally, Hypotheses will be developed to understand if and how network effects impact the adoption intention of the consumer. Lastly, the role of trust as a moderator will also be hypothesized to be tested in the experiment.

2.1. Technology Acceptance

The foundation stone of this research is the interaction between the innovation in technology and potential consumer, therefore, this research revisits the various theories and conceptual ideas built around the acceptance and adoption of technology by consumers.

Pontiggia & Virili (2008) devised the relationship between the acceptance of technology and network effects. Using an experiment to understand the relationship between both notions, they traced a positive relationship between the network effects of a technological product/service and its effect on the acceptance of technology. In other words, the higher the user perception and the number of users, the more the chances of users accepting and adopting the technology. To understand this influence in greater detail, we revisit Majumdar & Venkatraman (1998) who theorized that network effects influence three orders of decisions: adoption of new technology, selection of product and compatibility decisions. This substantiates the effect of network effects in impacting the first order of consumer decision making i.e., the adoption of new technology. Furthermore, the various models of technology acceptance and social influence concretize the relationship between network effects and consumer adoption of technology in a more intricate way, theoretically speaking.

Venkatesh et al. (2003) developed a model to understand the use and acceptance of Information and Communication Technology by consumers. They formulated the Unified Theory of Acceptance and Use of Technology model (UTAUT) to trace and discern the reasons why consumers adopt a certain Information and Communication Technology. This theory was devised using the various theories on technology adoption and acceptance that have been developed by scholars over the years. The models and theories include the Theory of Reasoned Action (Ajzen & Fishbein, 1980), the Technology Acceptance Model (Davis, 1989), The Motivation Model (Sundar et al., 2012), The Theory of Planned Behaviour (Ajzen, 1975), Innovation Diffusion Theory (Rogers, 1962), and Social Cognitive Theory (Bandura, 1960). For the purpose of relevance, this research only focuses on the nuances of Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

In the case of the UTAUT model, four attributes ascertain the consumer adoption decision: performance expectancy, effort expectancy, facilitating conditions and social influence (Venkatesh et al., 2003 as cited in Magsamen-Conrad et al., 2015). Performance expectancy refers to the benefits and advantages of a technology, as perceived by the user. Essentially, it is the perceived performance and usage value that a consumer derives from Information and Communication Technology. Whereas, effort expectancy refers to how easy is it to use a technology for the user. Furthermore, facilitating conditions refer to the degree to which a user perceives the technological infrastructure as a source of support in terms of enhancing their performance. Lastly, Social Influence is the impact that other people's use of the technology has on the user (Venkatesh et al., 2003).

The network effects measured in this research consider the perceptions of the consumer when they interact with an e-Learning platform advertisement. This brings the notion of performance expectancy and the idea of social influence into primary significance. Network effects enhance the usage value and perception of the consumer towards the technology, driving their adoption intention, as discussed in detail in the further sections.

2.2. Adoption Intention

Adoption Intention can be defined as a consumer's inclination to use or their willingness to adopt a product/platform/technology in the future. It is a marker of the probability or likelihood that a person will use or incorporate the product/platform/service in their lives (Kupfer et al., 2016). This research assesses the Adoption Intention Behaviour of the consumer to ascertain the role of network effects in influencing it.

The proposed model that this research intends to hypothesize is the consumer's acceptance of technology (Davis, 1989) as influenced by an Installed Base of users in the case of direct network effects and the number of compliments on the platform, in the case of indirect network effects. As mentioned earlier, technology acceptance is positively correlated with network effects and hence, leads to a higher network effect (Pontiggia & Virili, 2008). Therefore, this symbiotic relationship between technology acceptance and network effects could have a significant impact on consumer adoption intention. To assess the role of network effects, this research will assess adoption intention using the dependent variables: Installer Base for direct network effects and the perceived variety and quality of complimentary goods for indirect network effects. The impact of these two variables in influencing the adoption intention of the consumer has been assessed in this study using empirical research. Although to understand the notion of adoption intention, especially in the context of technology acceptance, it is also crucial to unravel the attribute of social influence as a key driver of adoption.

Social influence refers to the degree of influence that the adoption decision of a group has over an individual's adoption decision. According to the concept of Social Influence a person's degree of adopting a technology depends on or, is influenced by the individuals who are important to the consumer (Perera & Abeysekera, 2022). Therefore, the individual consumption decision is influenced by the consumption patterns of the people around the consumer. Magsamen-Conrad et al. (2015) have suggested consumers have the propensity to trust other users of technology while making adoption decisions, which will also be discussed in greater detail in further sections. Similarly, Chao (2019) hypothesized and proved via their research that performance expectancy, amongst many other factors like trust, positively influences the behavioural intention of the consumer. Performance expectancy has been defined as the degree of helpfulness of a technological innovation, as perceived by the consumer. It is positively related to the adoption intention of the consumer and hence, influences their decision to use and accept a technological innovation. Venkatesh et al (2003) as cited by Chao (2019) suggest that Performance Expectancy has the maximum strength in influencing the consumer adoption decision in the case of technological innovations. Therefore, the performance expectancy as perceived by the consumer and social influence around the consumer, affect their decision-making process for adoption of technologies.

While these factors have been scientifically and quantifiably studied concerning adoption intention, in the aforementioned studies, there has been a dearth of research when it comes to the influence of network effects on the adoption of technological innovation, especially e-Learning platforms. This research adds to the current literature by assessing the influence of the aforementioned attributes – social influence and performance expectancy in the form of direct and indirect network effects, and how they impact e-Learning platform adoption. It is also a pivotal time in the study to acquaint with the concept of e-Learning platforms and how they function.

2.3. E-Learning Platforms

E-Learning is a mechanism of using modern technological tools for education to facilitate a holistic and engaging learning environment by employing the Internet and other digital content for instructional activities (Ouadoud et al., 2021). Using an extensive variety of multimedia tools, e-Learning encourages a two-way conversation between the user and the course content provider and provides a channel for an innovative way of learning (Rawashdeh et al., 2021). Challenging conventional teaching mechanisms, e-Learning emphasises student engagement with the content of the course, which is usually provided by the internet and a content provider platform.

The increasing dependence on technology and, the surging demand for learning worldwide make e-Learning platforms an indispensable part of the modern-day education system. The advent of this mechanism of learning has paved the way for remote learning models in educational institutions. This model of learning contributes to increased comprehension amongst students and as a result improved retention of concepts. Moreover, this mechanism of learning has resulted in remote systems of learning where users/learners have the opportunity to learn with flexibility in terms of time and geography. E-Learning becomes instrumental, especially in the post-pandemic times, in supporting the graduated students who will be entering a hybrid work environment by helping them navigate the digital and virtual spaces of work (Cloud, 2022).

Furthermore, the new and upcoming generations, like GenZ, have been brought up surrounded by technological innovations leading to developing comfort with technology and a reduced attention span. This hinders the effectiveness of the conventional or traditional modes of learning and therefore, highlights the importance of innovative mechanisms of e-Learning (Stecula & Wolniak, 2022). Having established the meaning and relevance of e-

Learning, this study will delve deeper into the notion of adoption and the problem it faces in the case of e-Learning platforms.

2.4. Adoption of E-Learning platforms

In 2017, a report by the New Media Consortium Horizon suggested that blended and hybrid learning technologies have an effective impact on steering the adoption of technology for learning in higher education. The report also asserted that the impact is supposed to increase in upcoming years as the dependence on e-Learning platforms increases in the domain of higher education (Adams Becker et al. 2017). However, the adoption of e-Learning platforms persists to be a challenge as students worldwide are still hesitant to switch to virtual/online models of education (Hashem, 2011 as cited in Wang, 2014). It is imperative to understand the impediments on the road to high adoption of e-Learning technologies, and to propose a research model as a solution.

Several factors pose a challenge to the adoption of e-Learning platforms by students. Firstly, transforming your personal space into a classroom requires a sound information and communication technology infrastructure. This poses one of the biggest impediments, especially for people in developing countries as the ICT infrastructure is still not functional to its full potential (Mark-Oliver & Asiedu, 2010). Mutsiya & Makokha (2016) conducted a study to assess the challenges in the adoption of public universities in Kenya. They inferred that the lack of sound Information and Communication Technology (ICT) infrastructure serves as the biggest challenge for the student adoption of e-Learning platforms in developing countries like Kenya.

Furthermore, Ali et al., (2018) developed a conceptual framework, tracing the barriers to the implementation and adoption of e-Learning platforms. The researchers consolidated literature narrating 68 barriers to the implementation of e-Learning models. While the majority of reasons consisted of impediments fuelled by the lack of technological infrastructure, there have also been studies on students' hesitation in using e-Learning technologies (Nwabufo et al., 2013), and a lack of confidence and self-efficacy in using the platforms (Suleman et al., 2011). This discomfort with the technological infrastructure and hesitation to adopt e-Learning platforms has also exacerbated the digital divide between developed and developing countries (Suleman et al., 2011). The digital divide between developing and developed countries is accentuated by the differences in readiness, and trust and hence, affects the adoption of technology for learning.

Mutsiya and Makokha (2016), also suggested that there is a lack of awareness, reduced online interactions, and ineffective marketing efforts for e-Learning implementation, plummeting the adoption rates of e-Learning platforms among students. The lack of awareness about the platforms is also a result of ineffective marketing and communication efforts (Krizanova et al., 2019). This ineffectiveness in marketing results in the inability/failure to communicate the value of the e-Learning platform to prospective customers, resulting in a reduced adoption and usage of the platforms. Therefore, it is pivotal to formulate effective communication strategies which could affect the consumer's intention to adopt the e-Learning platform.

Lastly, from the perspective of companies making e-Learning innovations, the dearth of adoption creates an impediment in their way of reaching the critical mass of users. As per Roger's Diffusion of Innovation Theory, a critical mass is a certain number of adopters that ascertain if the adoption of the technological innovation in question can become self-sustaining or not (Byrd et al., 2021). Achieving the critical mass of users is pivotal for technological innovation to be coined as successful. David et al., (2020) suggested that instilling and attracting initial interest in the technology is one of the many impediments faced by technological innovation when it is in its pre-launch stages. Therefore, this postulates that it is important to focus on achieving a greater adoption number so as to make the technology innovation, accepted, successful and sustainable. In the next section, we discuss the notion of network effects and how it can overcome the aforementioned impediments, promising an effective way of boosting adoption.

2.5.Network Effects

'Network effect', also known as network externality, is the notion or a situation where the brand value increases of a particular product/service with the rise in the number of users or buyers. The higher the number of people engaged i.e., the number of buyers or people adopting that platform, the bigger the attractiveness of the platform (Stobierski, 2020). This section talks about these concepts and the underlying framework in larger detail.

2.5.1. Significance and Types of Network Effects

While Katz and Shapiro (1994) laid the foundation of the conceptual literature on network effects, Kato and Negoro (2007) expanded on the concept to build a theoretical framework. Their focus was not only on the mechanism of network effects but also, on the participants in the process whose growth is simultaneous with that of the network effect.

They conceptualised the idea and traced the three entities that are involved in the nexus of network effects: the users, complementors and platform leaders. Network effects are generated amongst the platform leaders and users and, complementors and users, as more and more users adopt the technology.

A significant example of this concept is PayPal, a company which harnessed the power of network effects to enhance value and dominance in the financial services industry. PayPal is an online payment service which enables individuals and businesses to transfer money online for their transactions. It is an effective payment mechanism which ensures security and allows flexibility, making it an indispensable asset in the financial services industry (Rusu & Simion, 2019). The diffusion of PayPal was a result of giving strategic significance to network effects and developing initial diffusion strategies like discounts, giveaways, offers, etc. to subsidize the consumer adoption of the platform. The focus on network effects to influence adoption worked in PayPal's favour and they were able to acquire a significant market share by garnering a good number of adopters. This early adoption led to PayPal being one of the largest used platforms for financial transactions (University of Minnesota, 2015).

Conceptually, Kato (2016) suggests that a positive network effect is a signifier that a product or service is blooming in the industry. Especially in the case of technological platforms and services, they become a metric of success as a positive network effect contributes to enhancing the value of the product/service/platform for the user. The notion of network effects has been segmented into two categories as per the way and form in which they interact with the potential users of a technological platform/service/product. Katz & Shapiro (1994) mapped these into direct network effects and indirect network effects.

Direct network effects entail the growth of a network/service/product because of an increase in the number of overall users. The network, in this case, grows by itself as it gathers a large base of users (Stobierski, 2020), examples include Whatsapp, Skype, etc. Klemper (2008) as cited in Kim et al., (2022), suggests that the increase in the value of a product/service for a user, as a result of other people using it, gives rise to direct network effects and also serves as an increased incentive for the user. Whereas, in the case of indirect network effects, a platform/service/product functions between two or more user groups (Stobierski, 2020), and the supply and demand by both groups affect each other (Stremersch et al., 2007). Examples of indirect network effects include iOS and Windows' growth because of the increasing usage of hardware systems. With the rising usage of hardware technologies like Laptops and smartphones, the adoption of complementary software technologies also increases. For instance, somebody buying an HP Laptop would also be adopting and using the Windows system, which serves as a complementary good in this case (Reddy, 2018)

Network effects' influence in driving consumer adoption decisions has been tested in the past in the case of various platform products/services. Steiner et al. (2015) conducted a study to investigate the heterogeneity and the role of network effects in the video game console market. They concluded that network effects work in different ways across the various segments of consumers in the video game console market. Hence, the paper suggests that marketers should consider the impact of network effects and how it intertwines with consumer heterogeneity to drive adoption (Steiner et al., 2015).

Similarly, Kumar et al., (2021) conducted a study to understand the adoption of platform-based mobile payment systems in emerging and developing countries. In the research, they tested the role and impact of country-wide heterogeneity and network effects to understand the consumer adoption behaviour of mobile wallet systems. They also recognized the presence of network effects, amongst other variables, driving the adoption among consumers (Kumar et al., 2021).

This research focused on both network effects and their impact on the technology adoption decision for the consumer in the e-Learning platforms industry. Investigating the role of direct network effects on the adoption of e-Learning platforms entails if the current installed base of users of e-Learning platforms impacts the adoption intention prospective buyers. In the case of indirect network effects, the consumer's perception of the variety and quality will be assessed to understand its significance on the consumer adoption decision, as these antecedents serve as the measurement for complimentary content providers i.e., the impact of indirect network effects. Therefore, we elucidate these concepts in detail in the further sub-sections.

2.5.2. Perceived Installed Base of Users

The concept of an Installed Base of users can be defined as the number of installations or subscriptions that the product has after being launched into the market (Aanestad et al., 2017). Koski (1999) empirically tested the significance of the Installed base of users in the larger network externality framework and found that a high number of prior adopters of a platform/product/service has a positive influence on increasing market share. Steiner et al.,

(2015) also suggest that an increase in the number of users on a platform or service leads to a rise in the channels of communication, thereby increasing the opportunity to interact. Schilling (1999) also suggests that the size of the installed base of users of a platform determines the success or failure of a company. Smallwood & Conlisk (1979) as cited by Song et al. (2009) state that an increased installed base is also a signal for the product quality and hence contributes to the usage intention of the consumer. It is also significant to note that a large installed base of users serves as an indicator of viability and certainty since it instils trust in the consumer that investment in the given product/service will be beneficial (Brynjolffson & Kemerer, 1996 as cited by McIntyre, 2011). However, Suarez (2005) conducted an empirical study and suggested strong ties network effects are a key determinant for technology adoption, especially in cases where technologies compete with each other. In simple terms, network effects which are generated within a potential consumer's close circle or as a result of strong tie association serve as a key driver of adoption of technology, especially if the technology is situated in a highly competatitve market.

Therefore, to assess the impact of direct network effects on e-Learning adoption, this research focuses on how consumers perceive the size of the installed base of users of a platform, assessing its impact on their adoption intention. On the other hand, indirect network effects entail an impact on the consumer's adoption intention by the number, variety and quality of complimentary goods and services, as explained in the section further.

2.5.3. Complimentary Goods

Indirect network effects are driven by the availability of complementary goods/services available in the market. As two or more products/services are dependent on each other in the network market, the usage and value of one impact the adoption of the other (Stobierski, 2020). Taking the case of the video game console market, Cenamor et al. (2013) elucidated that consumer adoption of a platform is influenced by the number of complimentary goods/services available on the platform. Steiner et al. (2015) suggest that the increase in the number, variety and quality of complementary goods/services on the platform directly influences the value and adoption of the platform. At the same time, it is the perceived variety and quality of the complementors, by the consumer, that provides a measure of the impact on adoption intention (Steiner et al., 2015)

2.5.3.1. Perceived Variety

Perceived Variety refers to the diversity and range of choices provided by a platform to the consumer. It is a metric to gauge how consumers rate the richness and diversity of choices on the platform's offerings. Platforms that offer a higher variety are perceived to be more appealing to users than the ones which have a low variety of choices (Kahn & Wansink, 2004). This study measures the perceived variety to measure the influence of complementors' indirect network effects in driving the adoption of e-Learning platforms. The scale for it has been discerned from Kahn & Wansink (2004) as cited by Steiner et al., (2015), which measures the effect of the perceived variety presented in the advertisement, as a part of the measurement instrument.

2.5.3.2. Perceived Quality

When discussing network effects, the term "perceived quality" refers to the subjective evaluation of the overall quality of a platform, which is affected by the existence of network effects. It is the measure of the quality of content provided by the complimentary content providers on the platform, in the case of e-Learning platforms. The perceived quality of a platform would be high if the consumer perceives the platform to be of high quality (Stylidis et al., 2020).

Therefore, to assess the influence of direct network effects on e-Learning platform adoption, this research attempts to empirically understand the impact of the size of the Installed Base of users on the consumer adoption decision in the case of e-Learning platforms. To assess this, the following Hypothesis is proposed:

H1: Installed Base has a positive impact on the adoption intention of e-Learning platforms.

The following hypothesis is formulated to empirically understand the impact of the availability of complimentary services/platforms on the consumer adoption decision of e-Learning platforms:

H2: The perceived variety and quality of complimentary content providers positively impact the consumer adoption intention of the e-Learning platform.

To assess these hypotheses, the research also evaluates the role of trust as a moderator. The concept and its relevance to this study are elucidated in the further sections in greater detail.

2.6. Trust

Researchers have defined trust as a complex concept which entails a set of expectations spread amongst inchoate groups of people, groups and institutions (National Academies Press (US), 2015). Especially in the case of online platforms, Trust plays a pivotal role in predicting the behaviour of a stakeholder or serves as a criterion for the selection of one, for the consumer (Aljazzaf et al., 2010). According to Eastlick and Lotz (2011), online trust can be defined as the degree to which a customer will accept vulnerability intently on an online vendor's legitimacy, goodness, and competence to keep its promises in the future. Online trust comes into being as a result of a consumer/person’s interaction with Information and Communication Technology (Wu et al., 2011). It is a sense of reliance that a prospective buyer has on the information provided to them by the vendor. Kamis and Zulkiffli (2020) elucidate that trust plays a pivotal role in the consumer’s intention to purchase/buy any product/service online and is also dependent on their trust in the platform/product/service, as well as the vendor.

There is a significant difference between trust in offline mechanisms of transactions and the ones that are online. In the case of offline buyer-seller relationships, trust is invested in human entities and is moderated amongst them (Doney & Cannon, 1997). However, in the case of online transactions, trust becomes a much more nuanced and complex idea, which involves reliance on the information provided to the potential consumer (Kim & Peterson, 2017). Furthermore, online initial trust has a significant impact on the purchasing decision and adoption intention of the consumer, in terms of persuading the consumer into buying the platform/service if the level of trust in the platform/service is high (Kim et al., 2007). Similarly, in the case of online transactions, a person’s propensity to trust/trustworthiness also plays a major role in influencing their intention to adopt.

Therefore, this research focuses on two elements of trust which are significant to the research question:

1. Propensity to Trust:_ Propensity to Trust is a measure of a person’s general trustworthiness. It signifies one’s perception of how trustworthy do they find other people/things/information to be and the ability to trust others in general (Rotter, 1967,

Mayer et al., 1995 as cited by Alarcon et al., 2018). A propensity to trust is usually the measure of a person's trustworthiness towards others and accounts for a personality trait as one grows up (Sitkin & Pablo, 1992). According to Lee & Turban (2001), Individual trustworthiness is a trait that is shaped by a person's cultural background, psychological makeup, and life experiences. Kim & Prakhar (2004), have devised that the propensity to trust in a person has an effect on the Initial Trust that a person has in the new technology.

2. Initial Trust: Mayer et al., (1995) define trust as the willingness/readiness of a person to be vulnerable to the activities of others, regardless of their capacity to observe or manage others. According to Kim & Prabhakar (2004), a consumer's initial trust in an electronic platform/service, or e-payment channels for e-commerce transactions, is positively correlated to the person's propensity to trust. This means that a generally trusting person would be able to trust the e-payment systems. Moreover, Kim et al., (2009) devised a positive correlation between the propensity to trust and initial trust in the mobile banking system stating that they share a symbiotic relationship and enhance each other's impact.

The initial trust in the platform is an antecedent of the Trust behaviour of a consumer, or a potential consumer in this case when they interact with technological innovation for the first time (Kim & Prabhakar, 2004). If the platform lives up to its trust expectations, it can be enhanced by the general trustworthiness of a person or the propensity to trust. The propensity to trust measures the ability of a person to be trusting a person or a thing in general and includes the social and cultural conditioning of a person as well (Mayer et al, 1989). On the other hand, Lippert & Davis (2006) traced the significance of initial trust in technology and a person's interpersonal trust in influencing their adoption behaviour. They suggest that these two antecedents of trust can amplify the adoption and acceptance of technology. Furthermore, Bahmanziari et al., (2016) conducted an exploratory study and suggested that trust is a pivotal factor in the acceptance and adoption of technology. They devised that consumer trust in the technology and their general trustworthiness are important factors, and can drive the adoption of technology efficiently. Furthermore, (Sun, 2017) theorized that initial trust in technology has an impact on the propensity to trust. Put simply, initial trust in technology, if built, affirms the consumer's sense of trustworthiness, resulting in an impact on the intention and actual use of technology by the consumer. Therefore, these two antecedents of trust will be measured as moderators in the research model.

Therefore, this study focuses on two components of trust – initial trust in technology and a person's propensity to trust, an antecedent/dimension of interpersonal trust (Zhang, 2021), and their impact on the relationship between network effects and the adoption of e-Learning platforms. In this research model, Trust acts as a moderating variable which is situated between the independent variable i.e., network effects and the dependent variable i.e., adoption intention and drives the relationship between both of them.

Therefore, the following hypotheses were formed:

H3: The relationship between direct network effects and consumer adoption intention of e-Learning platforms is moderated by Initial Trust in the platform and the person's propensity to trust.

H4: The relationship between indirect network effects and consumer adoption intention of e-Learning platforms is moderated by the Perceived Trust of the consumer and the Initial Trust in the platform

3. Methodology

This chapter provides an overview of the methodology for this research. The chapter contains a detailed overview of the sample population targeted for the research, the method of data collection, the operationalisation of variables, and the approach for data analysis.

3.1. Research Design

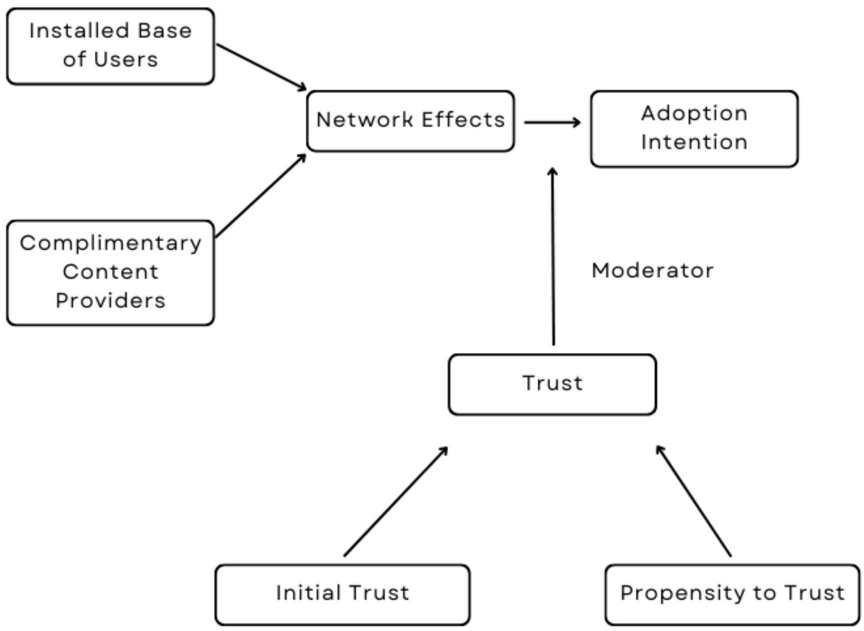

Figure 3.4.1. Research Model

3.2. Procedure

The measurement instrument, an experimental survey, consisted of advertisements centred around content highlighting direct and indirect network effects, followed by a series of questions to be answered by respondents on the basis of the ads, which were randomly assigned (refer to Appendix A). Following the instructions, the respondents have to carefully examine the advertisements and answer a series of questions which indicate whether or not they intend to adopt the e-Learning platform. Two independent variables will be used: The installed base of users and complementary goods.

Overall, the measurement instrument comprised four conditions out of which one would be randomly assigned to a respondent. The respondent had to go through the condition, which in this case is a poster, and respond to the questions that follow. The respondent was asked to go through the advertisement carefully and choose the appropriate answer option as per the statements given. The four conditions were based on the different levels of direct and indirect network effects that the advertisements focus on. The four conditions are as follows:

1. Low direct network effects and high indirect network effects.
2. Low indirect network effects and high indirect network effects.
3. Low direct and indirect network effects.
4. High direct and indirect network effects.

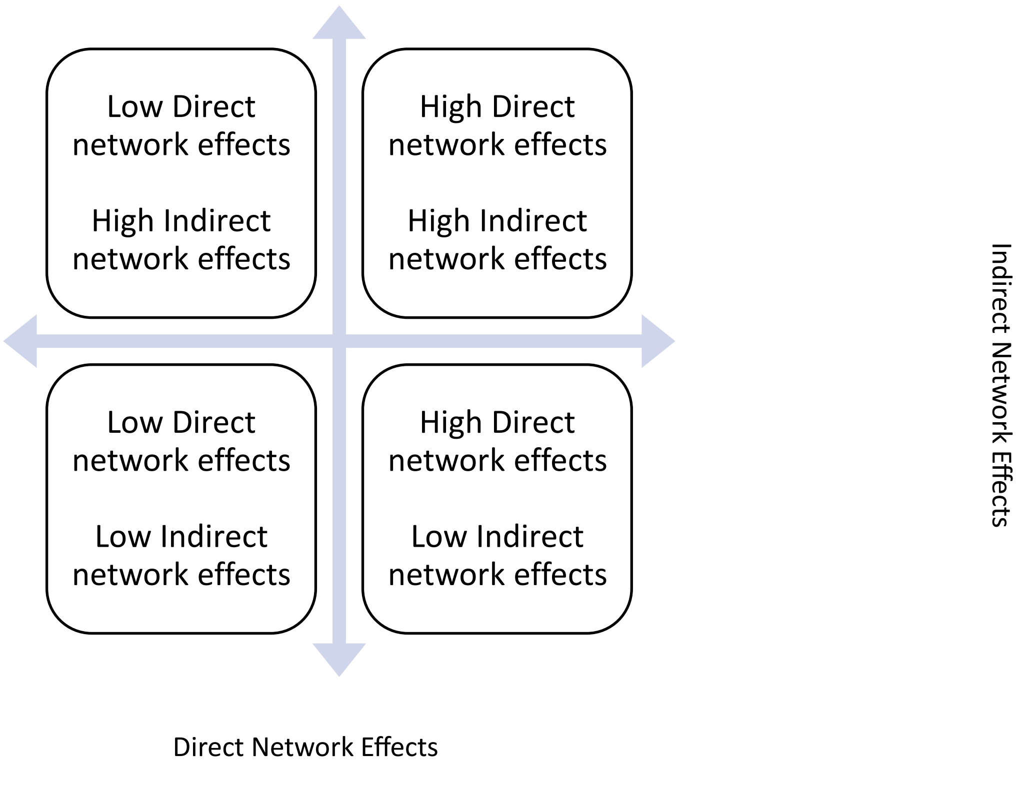

Figure 3.4.2. Conditions for manipulation

After the computation of variables, a hierarchicial multiple regression was conducted to assess if the relationship between the categorical independent variables i.e., Installed Base of Users and Complimentary Goods, and the dependent variables i.e., adoption intention is significant or not. A significant value of p (<0.05) indicates that there is a significant relationship between network effects and the intention to adopt. Whereas, if the p-value is >.05, it indicates that the relationship between network effects and intention of adoption is insignificant. Similarly, Hayes' moderation analysis was conducted to assess the significance of the interactions between the independent variables, moderating variable and the dependent variables. Both the analyses were conducted on the statistical programming software by IBM called SPSS.

3.3. Sample and data collection

The method of sampling chosen was a combination of purposive sampling and snowball sampling. Purposive sampling is the method of data collection where the respondents are chosen with prior knowledge and context and a specific purpose that the researcher might have in their mind (Qualtrics, 2022). Whereas, snowball sampling is used when the researcher wants to reach a larger target population through referrals (Qualtrics, 2022). For this project, a combination of both data collection methods is used to target a specific kind of population i.e., university students. The responses were recoded across four conditions which were randomly assigned to the respondents and therefore N=120 valid responses were collected in total.

The experimental survey was circulated amongst the students studying at Erasmus University Rotterdam, The Netherlands and Ashoka University, India. These institutions have been chosen for the convenience of the researcher since he is currently studying at Erasmus and is an alumnus of Ashoka University. Due to an initial lack of expectedly sufficient responses, the survey was circulated with students in the United States of America as well.

3.3.1. Measurement Instrument

As mentioned earlier, an experiment was conducted with four conditions using a survey on Qualtrics for data collection. Experiments are a way of conducting scientific research where one or more independent variables are changed and applied to one or more dependent variables to ascertain their impact on the latter (Zubair, 2023). An experiment has the ability and bandwidth to assess the evidence of causal relationships within the ambit of a research project or question (Neuman, 2014). The experiment was conducted using a survey, in which both independent variables – direct and indirect network effects were manipulated across four conditions, to assess their relationship with the dependent variable – Adoption Intention. The moderating variables – Initial Trust and Propensity to Trust, were also included in the structure of the survey to assess how they moderate the relationship between the independent and dependent variables.

The survey experiment was published on Qualtrics and was distributed amongst the respondents by way of social media channels/platforms like WhatsApp and Instagram.

For the analysis, the quantitative method of data analysis was chosen as the proposed method of study. Quantitative research is an effective tool of research and analysis which promulgates knowledge and understanding about the various complexities of the social world on measurable scales (Allen, 2017). Based on a targeted population, quantitative research allows the researcher to observe and measure data to delve deeper and analyse the results derived from the sample population (Allen, 2017).

The results derived from quantitative research can be used to derive causal relationships, understand patterns and enable a universalization of results to a larger population (Bhandari, 2022). After the computation of variables by deriving means from scale items, a hierarchical multiple regression analysis was conducted, along with Hayes' moderation analysis model 2, for Hypotheses testing. The appropriate reliability and validity test were also conducted to ensure the quality of the data and analysis. And before analysing the data for hypotheses testing, appropriate manipulation check were conducted to ensure the randomization of conditions.

3.4. Operationalisation and computation

3.4.1. Independent Variables

This research project intends to focus on two aspects of network effects, installed user base, to measure direct network effects and complementary content providers, to measure indirect network effects as independent variables. To assess the role of direct network effects, the respondents were asked about their perception of the Installed Base of Users on the platform. This question was measured on a 7-point Likert Scale where 1 = Very Low and 7 = Very High. For the indirect network effects, the respondents' behaviour towards the number of complimentary content providers was taken into consideration. A two-item scale was devised which had questions on the respondents' perception of the Variety of complimentary content providers (Kahn & Wansink, 2004) and Perceived Quality of complimentary content providers (Bearden et al., 2003) of the platform (Steiner et al., 2015).

3.4.2. Moderating Variables

To assess the role of trust in moderating the relationship between network effects and consumer adoption intention, a combination of scales was used. According to Edwards & Lambert (2007), a moderating variable impacts the relationship between the independent and the dependent variable in statistical research, by interacting with the independent variable. A moderating variable has the influence to change/direct the effect of the independent variable on the dependent variable by generating a moderating effect (Hair et al., 1998). There is usually a firm relationship between the independent and the moderating variable and the moderating effects strengthens the relationship between the independent and dependent variable (Farooq & Vig, 2017).

This research used Trust as the moderating variable in influencing/directing the relationship between network effects and the adoption intention of the consumer. The variable was measured using two scales – The initial Trust Scale and the Propensity to Trust Scale. The Propensity to Trust scale is a four-item scale which measures the trustworthiness of a person. The four-item scale facilitates the assessment of a person's ability to trust others or information, in general. The scale was devised by Mayer et al. (1995) to measure the trustworthiness of a person. The items included statements about the respondents' trustworthiness like "my tendency to trust a person/thing is high", and "Trusting someone or something is not difficult". These four statements were measured on a 7-point Likert scale where 1 = strongly disagree and 7 = strongly agree. The scale was revised to make it relevant to the current study.

The Initial Trust scale is a five-item scale devised by Kim et al., (2017). This scale measures the ability of a person to trust a technological innovation like payments through e-commerce channels. The scale required the respondents to respond to statements like "I trust this platform keeps my best interest in mind", "I believe in the information this poster provides me", etc. The responses to these statements were measured on a 7-point Likert scale where 1 = strongly disagree and 7 = strongly agree. Similarly, this scale was also revised to establish relevance with the current study.

3.4.3. Dependent Variable

The Adoption Intention of the consumer serves as the dependent variable. To measure Adoption Intention, a three-item scale from Grewal et al., (1998) was used. The scale was altered as per the conditions and layout of this research. Adoption Intention is considered a dependent variable and the scales for measuring were derived from Grewal et al., (1998) as cited by Steiner et al., (2015), to assess the Behavioural Intention with regards to the consumer perception of a platform

3.5. Reliability and Validity

To measure the consistency and stability of the research instrument, a test of reliability and validity was conducted. Internal consistency reliability was evaluated using Cronbach's alpha coefficient for each construct which was measured in the questionnaire. As recommended by DeVellis (2003), values greater than .70 were considered acceptable. All alpha values were shown to be reliable and ranged between .89 and .93, with Adoption Intention ($\alpha = .93$), Propensity to Trust ($\alpha = .89$), and Initial Trust ($\alpha = .91$). All the scales were deemed reliable and suitable for further analysis as no modifications were shown to significantly improve scale internal consistency (Appendix B).

To test the reliability of the independent variables, their dummy correspondents were created to measure if the manipulation was done correctly. Significant differences between the means of groups within both the independent variables were observed, advocating for the quality of data. The manipulation check is reported in section 4.2. in further detail.

4. Results

4.1. Sample characteristics

A total of 121 responses were recorded. However, 1 was excluded as the respondent had not completed the survey and hence, was deemed as invalid. After data cleaning 120 responses were included in the analysis.

The respondents belonged to several nationalities, mostly comprising Indian, Spanish and Dutch. There were respondents belonging to other nationalities too like American, Vietnamese, Mauritian, etc., which provided a diversity of respondents in the survey, in terms of nationality. The respondents also belonged to a variety of educational institutions from across the world but mostly comprised of students from Ashoka University, India and Erasmus University Rotterdam. The characteristics of age and gender have been detailed in Table 4.2.1. In terms of age, the majority of the respondents fall into the age group of 18-25 years i.e., 65%. Furthermore, while the maximum number of respondents expressed their gender as female comprising 63.30% of the total respondents, about 0.80% decided to not disclose their gender. (See Appendix C for detailed overview of sample characteristics).

Table 4.2.1 Sample Characteristics

Characteristic	Frequency in sample	Percentage of sample
Age (in years)		
18 – 25	78	65.00
25 – 40	42	35.00
Gender		
Male	40	33.30
Female	76	63.30
Non-Binary	2	1.70
Prefer not to say	1	0.80

4.2. Manipulation check

The measurement instrument consisted of four conditions which were randomly assigned to N=120 participants. The Independent variables i.e., direct network effects and indirect network effects were computed into their dummy correspondents to compare and examine the differences between the means of both variables. The computation of dummy variables was performed by assigning units 0 and 1 as per conditions. 0 was assigned to a low network effect and 1 to a high network effect, both direct (DDNE) and indirect (DINE), as per the conditions randomly assigned to the respondents.

Firstly, while comparing the means of Direct network effects and the dummy direct network effects, an independent samples t-test was conducted to examine the differences for N=120 respondents where Group (0) had a mean score of M=3.42 with a Standard Deviation of SD = 1.48, and Group (1) had a mean score of M = 4.55, with a Standard Deviation of SD = 1.62; $t(118) = -3.94$, $p = < .001$, showing significant differences between both groups.

Similarly, the means of Indirect network effects and its dummy correspondent were compared and examined. An independent samples t-test was conducted for N=120 respondents where Group (0) had a mean score of M = 3.70 with a Standard Deviation of SD = 1.30 and Group (1) had a mean score of M = 4.22 with a Standard Deviation of SD = 1.15; $t(118) = -2.35$, $p < .02$, showing a significant difference between both groups. Both t-tests with significant values of p advocate for the quality of the results. The significant t-tests postulate that variance was not assumed and differences in the mean scores between groups in dummy correspondents of independent variables are statistically significant.

4.3. Factor analysis and reliability analysis

In order to assess the dimensionality and underlying structure of the items, a Principal Components Analysis was performed. The scales were purified with an eigenvalue cutoff of 1.0 and factor loading cut-offs of 0.40. Each multi-item measure has Cronbach's alpha values that meet or exceed the cut-off. Appendix B lists all measures, the scales' Chronbach's alphas, and the factor loadings of items included in the multi-item measurements.

The 3 Likert-scale items for Adoption Intention were entered into factor analysis based on Principal Components extraction with Direct Obliminal rotation, confirming that a single factor explained 87.64% of the variance (KMO = .71, $\chi 2$ (N = 119, 3) = 293.76, $p < .001$). Reliability analysis indicated a very high internal consistency ($\alpha = .93$).

Similarly, the 5 Likert-scale items were entered into factor analysis based on principal components extraction with Direct Obliminal rotation, confirming that a single factor explained 37.30% of the variance in Initial Trust (KMO = .88, $\chi 2$ (N = 119, 10) =, $p < .001$). Reliability analysis indicated a very high internal consistency ($\alpha = .91$).

The 4 Likert-scale items were entered into factor analysis based on principal components extraction with Direct Obliminal rotation, confirming that a single factor explained 30.10% of the variance in Propensity to Trust (KMO = .74, $\chi 2$ (N = 119, 6) =, $p < .001$). Reliability analysis indicated a high internal consistency ($\alpha = .89$).

4.4. Descriptive statistics and correlations

To evaluate the relationship between variables, Pearson's Correlation test was conducted. The results have been reported in Table 4.4.1 which consists of the mean, standard deviation and correlations of each variable. The dependent variable, Adoption Intention had a significant, positive and weak relationship with direct network effects ($r = .42$) with $p = .09$. Similarly, the association between adoption intention and indirect network effects would also be considered as significant, positive and weak ($r = .52$) and $p < .001$.

In the case of moderating variables, the propensity to trust has a significant, positive yet weak association with adoption intention ($r = .20$) with $p = .30$. Similarly, in the case of initial trust in the platform, a significant, positive and weak association was reported ($r = .54$) with $p < .05$, with adoption intention. Furthermore, a weak association was also reported between the independent variables i.e., direct and indirect network effects ($r = .62$). The correlation between the moderating variables i.e., Initial Trust and Propensity to trust was also significant, positive and weak ($r = .35$). There was a very weak correlation between the dummy correspondents of independent variables and adoption intention i.e., Dummy direct network effects ($r = .17$) and dummy indirect network effects ($r = .11$).

Table 4.4.1 *Descriptive statistics and correlations (n = 120)*

	1	*2*	*3*	*4*	*5*	6	*Mean*	*S.D.*
1. Adoption intention	-						3.50	1.65
2. Direct network effects	.42**	-					3.90	1.63
3. Indirect network effects	.52**	.62**	-				4.00	1.23
4. Propensity to trust	.20*	.14	.25*	-			3.70	1.27
5. Initial trust	.54**	.52**	.77**	.35**	-		4.30	1.25
6. Dummy direct network effects	.17	.34**	.22*	-.08	.07	-	.41	.50
7. Dummy indirect network effects	.11	.11	.21*	-.01	.11	.20*	.60	.50

*p ≤ .05, (2-tailed)

**p ≤ .01, (2-tailed).

4.5. Hypotheses Testing

To test Hypotheses 1,2,3 and 4 a hierarchical multiple regression analysis and Hayes' moderation model 2 analysis was conducted on SPSS. To include the effects of the conditions randomly assigned to the participants, moderation analysis was conducted twice with the dummy correspondents of both Independent Variables. The dummy correspondents of independent variables were simultaneously added as covariates (for instance Dummy indirect network effects as a covariate while tracing the interaction of Dummy direct network effects with trust variables) to control the possible influences of one variable over the other. A summary of findings has also been recorded in Table 4.5.1.

In the second model, the analysis was conducted with the dummy correspondent of direct network effects (DDNE) as the independent variable and the indirect network effects (DINE) as the co-variate, with Adoption Intention (AI) as the dependent variable and both the moderating variables i.e., Initial Trust and Propensity to Trust. The results of the analysis were insignificant (B = .20, Bse = .24, t = .82, p = .41). Similarly, another moderation analysis was conducted with DINE as the independent variable and DDNE as the covariate. the results were found to be insignificant (B = .26, Bse = .22, t = 1.15, p = .25). Hence, H3 is rejected.

Similarly, in the case of the indirect network effects dummy correspondent, the results were recorded by tracking the interactions between DINE and the moderating variables. In the case of DINE's interaction with Initial Trust, the results were insignificant ($B = .12$, $Bse = .22$, $t = .53$, $p = .60$). In the case of interaction with Propensity to trust, the results were insignificant ($B = -.11$, $Bse = .22$, $t = -.51$, $p = .61$). Hence, H4 is rejected

Lastly, a hierarchical multiple regression analysis was conducted with the Perceived Installed Base of Users and Adoption Intention as criteria in order to examine if Direct Network Effects impact the consumer adoption intention for e-Learning platforms. And, perceived variety and quality of complimentary content providers in the case of indirect network effects.

The model was found to be insignificant, $F(2, 113) = 2.10$, $p = .23$, and explained the total variance by 33.0%. The perceived Installed Base of Users was not found to be a positive predictor ($\beta = .12$, $p = .23$) of consumer adoption intention and therefore H1 is rejected.

In the case of indirect network effects, the results were insignificant, $F(2, 113) = 2.10$, $p = .30$, and explained the total variance by 33%. The perceived variety and quality of complementary content providers were not found to be a positive predictor ($\beta = .15$, p) of consumer adoption intention and therefore, H2 is rejected.

Table 4.5.1. Hierarchical Regression and Moderation Analysis with Adoption Intention as the dependent variable.

	Model		
	1	2	3
Main effects			
Dummy direct network effects (DDNE)	.52	.45	.24
Dummy indirect network effects (DINE)	.23	.10	.06
Initial trust		.11**	.45*
Propensity to trust		.42	.04
Direct network effects			.12
Indirect network effects			.21
Moderating effects			
DDNE x IT			.20
DDNE x PT			-.10
DINE x IT			.12
DINE x PT			.10
R^2	.04	.31**	.33
F-statistic	2,12	2,16**	2,10
R^2 change	.04	.28	.03
F-change statistic	2.20	22.60**	2.10

n=120, * p < .05, ** p < .001

Table 4.5.2. Hypotheses Testing Summary

Hypothesis	**Result**
H1: Installed Base has a positive impact on the adoption intention of e-Learning platforms.	Rejected
H2: The availability of complimentary content providers positively impacts the consumer adoption intention of the e-Learning platform.	Rejected
H3: The relationship between direct network effects and consumer adoption intention of e-Learning platforms is moderated by Initial Trust in the platform and the person's propensity to trust.	Rejected
H4: The relationship between indirect network effects and consumer adoption intention of e-Learning platforms is moderated by the Perceived Trust of the consumer and the Initial Trust in the platform.	Rejected

5. Discussion

The present study offers insights into consumer adoption behaviour towards e-Learning platforms by assessing the impact of network effects in influencing the adoption intention of the consumer. It also takes into account the concept of Trust as a moderator. The consumer's propensity to Trust and the Initial Trust in the platform served as the moderating variables for this study. The results suggested an insignificant relationship between network effects, both direct and indirect, and the adoption intention of the consumer. The insights from this study are instrumental in understanding the complexities of e-Learning adoption and the impact of factors like network effects and trust on the adoption intention of the consumer. It can be pivotal for e-Learning platform service providers to strategize their marketing and communication efforts to influence e-Learning platform adoption amongst consumers. The study also provides academic insights for understanding the problem of the lack of e-Learning platform adoption and provides a model for further exploration of the factors that impact adoption. This section focuses on discerning these insights, both practical and theoretical, and developing key learnings and implications from this study.

5.1. Theoretical Implications

The results of this study have theoretical implications which contribute to the ongoing academic debate/deliberation around the factors affecting the consumer adoption of technological innovations. Firstly, this study fills in the gap in the e-Learning adoption literature by empirically investigating the role of network effects as a factor that could impact the adoption intention of the potential consumer. There have been studies in the past which focused on information acquisition (Chen et al., 2012), policy and pedagogical changes (Barton, 2013), social factors and perceived usefulness (Olasina, 2019), etc. as influences of e-Learning platforms reaching their full adoption potential. However, with H1 and H2 being insignificant, the study also challenges previous research which suggests that network effects are primary drivers of technology adoption (Pontiggia & Virili, 2008).

Furthermore, the research is also substantiating the findings of Suarez (2005) who postulated that strong ties network effects are a key determinant for technology adoption, especially in cases where technologies compete with each other. Their study also suggested that the network effects research needs to move beyond the idea of using 'N' as the installed base of users and delve deeper into the various heterogeneities of the web of network effects, and the characteristics of the technology in question. The current research supports their argument by suggesting that the installed base of users, in the case of direct network effects, is not a primary driver of e-Learning platform adoption. Furthermore, it also challenges the previous academic research by Koski (1999) who suggested that a high number of prior adopters positively influence the potential adopters of the technological platform. The current study's findings postulate that a large installed base of users, by itself, does not have a significant impact on the adoption intention. This might be for a variety of reasons and a significant one could be heterogeneity of technological platforms. E-Learning platforms are different in their nature and characteristics from technological platforms which have witnessed a significant influence of network effects in increasing their adoption like video games (Steiner et al., 2015), social media applications like Whatsapp (Kim et al., 2022) or mobile payment systems (Kumar et al., 2021).

It also challenges the findings of the study by Schilling (1999) who suggested that the size of the installed base of users determines the success/failure of the company. The current study suggests that network effects are not the primary drivers of e-Learning platform adoption and hence, are not the primary marker of the success or failure of a company. Additionally, there also might be a possibility that in terms of adoption, there might be other drivers like the perceived usefulness of the platform (Jung et al., 2008; Moghadam & Bairamzadeh, 2009), perceived ease of use (Moreno et al., 2017, Mousa et al., 2020), etc. which still maintain their position as primary drivers of e-Learning adoption.

Secondly, this study also challenges the literature on technology acceptance and adoption. For instance, the research by Pontiggia & Virili (2008) provides empirical insights which suggest a positive relationship between network effects and the adoption of technology. This research challenges the aforementioned research by providing empirical evidence that network effects are not a primary driver in the case of e-Learning platform adoption. However, there is a scope for further investigation by using other forms of technology as well and considering consumer heterogeneity in adoption intention.

Furthermore, a very interesting theoretical insight provided by this study was the role of propensity to trust and initial trust, in moderating the relationship between network effects and e-Learning platform adoption. As opposed to Hypotheses – H3 and H4, the results of the analysis turned out insignificant implying that propensity to trust and initial trust either do not moderate the relationship between network effects and e-Learning platform adoption or their role is insignificant. This result provides us with multiple implications. This suggests that trust, when it interacts with the independent variables i.e., network effects, does not direct/change or impact the relationship between network effects and the adoption intention of the consumer, in the case of e-Learning platform adoption.

This finding suggested by the study challenges other studies like Bahmanziari et al., (2016), who suggested that trust serves as an important factor in technology acceptance and adoption. While their research talks about technology adoption and acceptance at large, the results of the current study challenge their findings and also delve deeper into understanding adoption behaviour with respect to the type and characteristics of the technology. The results of the current study, when compared with the previously mentioned studies, could also imply that the role of trust as a component driving adoption of technology could vary across different forms of technologies. For instance, the trust serves as an important component to drive consumer adoption in the case of tourism apps (Hua et al., 2021), cloud services (Rahi et al., 2017), etc. However, it is not the case with e-Learning platforms and therefore, this challenges the applicability of the aforementioned models and previous studies which postulate the moderating role of trust in technology adoption.

On the other hand, the finding substantiates the results of a previous study (Almajali et al., 2016), which ascertained that trust in e-Learning does not impact the actual use of e-Learning among university students. These findings could also be considered while assessing the applicability and relevance of the technology acceptance model and the unified theory of acceptance and use of technology model. Therefore, the role of trust could also be tested differently which is discussed in greater detail in sub-section 5.3.

5.2. Practical Implications

In its very essence, a high network effect signifies a high number of people adopting a particular platform, which results in an elevation in the brand value of the platform (Stobierski, 2020). This implies that firms curating e-Learning platforms can strategize their marketing communication efforts to boost network effects which will enhance the credibility of the platforms and lead to a rising user scale (Zhou & Van, 2022). However, this is not the case with e-Learning platforms. The current study proposes that network effects are not the primary drivers/influencers of the adoption intention of the consumer. In simple terms, an increased focus on communication, which is oriented towards advertising the user scale, by e-Learning marketers cannot help leverage high adoption numbers. Therefore, marketing practitioners would need to diversify their communication strategies in terms of tapping the primary drivers of adoption like perceived usefulness or perceived ease of use, in their marketing and advertising efforts. Furthermore, these diversified strategies could be used in the case of e-Learning platforms to understand the key factor influencing the initial adoption of the platforms.

Secondly, it is pivotal for technological innovations to acquire a critical mass of users to be coined as successful. The critical mass of users is defined as a certain number of users which is satisfactory for a company to ascertain the success of their technological innovation (Gruenbaum, 2015). David et al., (2020) suggested that instilling and attracting initial interest in the technology is one of the many impediments faced by technological innovation when it is in its pre-launch stages. However, an increased focus on network effects will not able to gather the critical mass of users, as per the results of this study. Therefore, as mentioned earlier, another goal of diversified marketing communication can be attaining the critical mass of users and perhaps then network effects could be tested to drive adoption further.

Furthermore, with H2 being insignificant, this study illustrates that potential adopters are not attracted towards the platform with merely the number and variety of complimentary content providers. Therefore, it is significant for marketers to focus on other aspects of the complimentary content providers like the quality of content, engagement and interface, brand value etc. as factors that could drive initial adoption instead of network effects. For instance, Ray et al., (2022) suggested that it suggested that it is significant to provide an engaging teaching network and boost peer support in the learning process so as to keep the students engaged and ensure sustainable adoption of e-Learning environments.

COVID-19 brought the world to a halt and compelled the education infrastructure to be moved online around the world. Universities, colleges, and other institutions can market their e-Learning platforms amongst students by using an innovative and diverse range of factors which influence e-Learning adoption positively.

5.3. Limitations and Suggestions for further research

The first limitation of this study is the bias that might be caused due to sampling method. The study used a combination of purposive sampling and snowball sampling for data collection. Firstly, the results drawn from purpose sampling cannot be extended to the entire population. Rather, they can only be applied to the sub-population from where the sample was taken (Andrade, 2020). This means that the results of this study are only applicable to university students between the age group 18-40, studying at universities/institutions in India, The Netherlands and the United States of America. Furthermore, while snowball sampling is a resourceful method to extensively target the population remotely, it is also susceptible to bias and could result in the underrepresentation of certain groups or perspectives. This could result in a limited understanding of the sample population being studied, a lack of diversity and can limit the generalizability of the findings.

Furthermore, while the moderating variables – the propensity to trust and initial trust in the platform were selected as per the suitability of the study, more antecedents of trust could have also been taken into account. Some of the antecedents include perceived risk behaviour, perceived usefulness, etc (Sarkar et al., 2020) could have also been included in the research to test if they moderate the relationship between the independent and the dependent variable, or could have also been considered as control variables.

There is also a probability that this research has been affected by Omitted Variable Bias. It refers to the kind of bias which occurs when variables, which might have a potential effect on the dependent variable, are omitted from the research model (Busenbark et al., 2022). Other variables could have also been considered for this research which could have played a role in this research model for instance, other antecedents of trust like perceived risk, or perceived usefulness could have been used to test the relationship between network effects and adoption intention. Moreover, other variables which directly impact the adoption intention for e-Learning platforms could have been included in the research to assess the results and statistical significance of network effects.

Furthermore, this research model could also be tested on other stakeholders in the e-Learning ecosystem like academics, educational institutions, etc. to understand the adoption intention trends of diverse audiences. It could be deployed to evaluate if network effects have an impact in boosting adoption when contextual factors like university-led programs, infrastructure readiness, and competing e-Learning platforms are taken into consideration. The external validity of the study could also be enhanced by spreading the sample population across different geographical locations. The current study was majorly based in The Netherlands and India (see Appendix C). It could also be conducted by people across different countries to also account for geographical factors like infrastructure readiness, perceived behaviour, attitude towards technology, etc.

Lastly, for further research, the model could also be assessed by including aspects like brand names to empirically understand the importance of brands in the relationship between network effects and the adoption of e-Learning platforms. This suggestion goes in line with the rejection of H2 where perceived variety, number and quality of complimentary content providers were taken as criteria, along with adoption intention. This could be enhanced by adding the brand name for the platform to assess if that drives the adoption intention of the consumer.

This current study aimed to understand the role of network effects in driving the adoption of e-Learning platforms amongst consumers, with trust as a potential moderating factor. The empirical analysis yielded some insightful findings that allow us to evaluate if network effects are the primary drivers for the consumer adoption of e-Learning platforms. To answer the research question, the results of this study indicate that network effects have an insignificant influence in driving the adoption of e-Learning platforms among university students and they also question the role of trust as a moderator between network effects and adoption intention. These findings could be fruitful for academics to further their understanding of consumer adoption behaviour in the domain of e-Learning and, for marketing practitioners to strategically communicate to their audiences, keeping in mind the factors that influence the consumer’s adoption intention. The research model could also be used to understand the e-Learning adoption nexus using other factors which have the potential to influence the consumer’s adoption intention.

References

Aanestad, M., Grisot, M., Hanseth, O., Vassilakopoulou, P. (2017). *Information infrastructures and the challenge of the Installed Base*. In: Aanestad, M., Grisot, M., Hanseth, O., Vassilakopoulou, P. (eds) Information Infrastructures within European Health Care. Health Informatics. Springer, Cham. https://doi.org/10.1007/978-3-319-51020-0_3

Almajali, D. A., Masa'deh, R., & Al-Lozi, M. (2016). Determinants of the actual use of e-Learning systems: an empirical study on Zarqa University in Jordan. *Journal of Social Sciences*, *5*(2), 1–29. https://works.bepress.com/raed-masadeh/4/download/

Aljazzaf, Z. M., Perry, M., Capretz, M. A. M. (2010). Online trust: Definition and principles. *Fifth International Multi-conference on Computing in the Global Information Technology*. 163-168. doi: https://doi.org/10.1109/ICCGI.2010.17

Allen, M. (Ed.) (2017). *The sage encyclopaedia of communication research methods*. (Vols. 1-4). SAGE Publications, Inc, https://doi.org/10.4135/9781483381411

Andrade, C. (2020). The inconvenient truth about convenience and purposive samples. *Indian Journal of Psychological Medicine*, *43*(1), 86–88. https://doi.org/10.1177/0253717620977000

Aristovnik, A., Keržič, D., Tomaževič, N., & Umek, L. (2016). Determining factors of students' perceived usefulness of E-Learning in higher education. *International Association for Development of the Information Society*.

Bahmanziari, T., Pearson, J. E., & Crosby, L. (2016). Is Trust important in technology adoption? A policy capturing approach. *Journal of Computer Information Systems*, *43*, 46–54. https://www.tandfonline.com/doi/abs/10.1080/08874417.2003.11647533

Barton, S. M. (2013). Social capital framework in the adoption of e-Learning. *International Journal on E-Learning*, *12*(2), 115–137. http://dro.deakin.edu.au/eserv/DU:30051852/barton-socialcapital-2013.pdf

Benajiba, N., & Eldib, R. S. (2018). Exploring attitudes related to sweetened soft drinks consumption among adults in saudi arabia. *Nutrition & Food Science, 48(3)*, 433–441. https://doi.org/10.1108/NFS-01-2018-0020

Bhandari, P. (2022, November 24). *What Is Quantitative Research? | Definition, Uses & Methods*. Scribbr. https://www.scribbr.com/methodology/quantitative-research/

Brika, S. K. M., Chergui, K., Algamdi, A., Musa, A. A., & Zouaghi, R. (2022). E-Learning research trends in higher education in light of COVID-19: A bibliometric analysis. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.762819

Busenbark, J. R., Yoon, H. (Elle), Gamache, D. L., & Withers, M. C. (2022). Omitted variable bias: Examining management research with the impact threshold of a confounding variable (ITCV). *Journal of Management*, *48*(1), 17–48. https://doi.org/10.1177/01492063211006458

Brynjolfsson, E., & Kemerer, C. F. (1996). Network externalities in microcomputer software: an econometric analysis of the spreadsheet market. *Management Science, 42(12), 1627.* https://doi.org/10.1287/mnsc.42.12.1627

Carlson, L., Portman, T., & Bartlett, J. (2006). Professional school counsellors' approaches to technology. *Professional School Psychology, 9,* 252–256. doi: https://doi.org/10.5330/prsc.9.3.9162536405845454

Cenamor, J., Sjödin, D. R., & Parida, V. (2017). Adopting a platform approach in servitization: Leveraging the value of digitalization. *International Journal of Production Economics*, *192*, 54–65. https://doi.org/10.1016/j.ijpe.2016.12.033

Chen, Y., Little, H., Ross, M., & Zhou, E. (2012). Factors motivating the adoption of e-Learning technologies. *Journal of E-Learning & Higher Education*, 1–17. https://doi.org/10.5171/2012.777468

Chen, J. (2022). Applying TAM to the adoption of e-Learning platform. *Proceedings of the 2022 3rd International Conference on Mental Health, Education and Human Development (MHEHD 2022)*. https://doi.org/10.2991/assehr.k.220704.207

Clay, M. N., Rowland, S., & Packard, A. (2008). Improving undergraduate online retention through gated advisement and redundant communication. *Journal of College Student Retention: Research, Theory & Practice*, *10*(1), 93–102. https://doi.org/10.2190/CS.10.1.g

Cloud, L. (2022, October 14). Three benefits of remote learning for every generation. *Forbes*. https://www.forbes.com/sites/forbesbusinesscouncil/2022/10/14/3-benefits-of-remote-Learning-for-every-generation/

David, R., Aubert, B. A., Bernard, J., & Luczak-Roesch, M. (2020). Critical mass in inter-organizational platforms. *ResearchGate*.

Davis, F.D. (1986) A Technology Acceptance Model for empirically testing new end-user information systems: Theory and results. *Sloan School of Management, Massachusetts Institute of Technology.*

Deslonde, V., & Becerra, M. (2018b). The Technology Acceptance Model (TAM): Exploring school counsellors' acceptance and use of Naviance. *The Professional Counsellor*, *8*(4), 369–382. https://doi.org/10.15241/vd.8.4.369

Doney, P. M., & Cannon, J. P. (1997). An examination of the nature of trust in buyer-seller relationships. *Journal of Marketing*, *61*(2), 35–51. https://doi.org/10.2307/1251829

Donnelly, R. & McAvinia, C. (2012). Academic development perspectives of blended learning. *In Anastasiades, P.S. (Ed.), blended learning environments for adults: evaluations and frameworks,* 1-18. Hershey, PA: IGI Global. 2012.

Eastlick, M. A., & Lotz, S. L. (2011). Cognitive and institutional predictors of initial trust toward an online retailer. *International Journal of Retail & Distribution Management*, *39*(4), 234–255. https://doi.org/10.1108/09590551111117527

Geith, C., & Vignare, K. (2008). Access to education with online learning and open educational resources: Can they close the gap? *Online Learning*, *12*(1). https://doi.org/10.24059/olj.v12i1.39

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. *Journal of Marketing, 62(2),* 46–59.

Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling [White paper]. Retrieved from http://www.afhayes.com/ public/process2012.pdf

Heli A. Koski (1999) The installed base effect: Some empirical evidence from the microcomputer market, economics of innovation and new technology, 273-310, doi: 10.1080/10438599900000012

Hrastinski, S., 2008. What is online learner participation? A literature review. *Computers & Education, Vol. 51,* 1755–1765

Hua, C., Cole, S., & Xu, N. (2021). Rethinking trust in tourism apps: the moderating effect of age. *Journal of Hospitality and Tourism Technology*, *12*(3), 548–562. https://doi.org/10.1108/jhtt-01-2020-0013

Jones, T. L., Baxter, M. A., & Khanduja, V. (2013). A quick guide to survey research. *Annals of the Royal College of Surgeons of England*, *95*(1), 5–7. https://doi.org/10.1308/003588413X13511609956372

Kamba, M. (2009). Problems, challenges and benefits of implementing e-Learning in Nigerian universities: An empirical study. *International Journal of Emerging Technologies in Learning (iJET)*, *4*(1), 66-69. Doi: https://doi.org/10.3991/ijet.v4i1.653

Kamis, F. F., & Zulkiffli, W. F. W. (2020). Online trust development in online shopping. *Journal of Information System and Technology Management*, *5*(18), 26–32. https://doi.org/10.35631/jistm.518003

Katona, Z., Zubcsek, P. P., & Sarvary, M. (2011). Network effects and personal influences: The diffusion of an online social network. *Journal of Marketing Research*, *48*(3), 425–443. https://doi.org/10.1509/jmkr.48.3.425

Katz, M. L., & Shapiro, C. (1994). Systems competition and network effects. *Journal of Economic Perspectives*, *8*(2), 93–115. https://doi.org/10.1257/jep.8.2.93

Kim, J., Newberry, P., Wagman, L., & Wolff, R. (2021). Local network effects in the adoption of a digital platform*. *Journal of Industrial Economics*, *70*(3), 493–524. https://doi.org/10.1111/joie.12296

Kim, Y., & Peterson, R. A. (2017). A Meta-analysis of online trust relationships in e-commerce. *Journal of Interactive Marketing*, *38*(1), 44–54. https://doi.org/10.1016/j.intmar.2017.01.001

Kimwise, A. (2017). Adoption of e-Learning technologies in education institutions/organizations: A literature review. *Kampala International University*.

Krizanova, A., Lăzăroiu, G., Gajanova, L., Kliestikova, J., Nadanyiova, M., & Moravcikova, D. (2019). The effectiveness of marketing communication and importance of its evaluation in an online environment. *Sustainability*, *11*(24), 7016. MDPI AG. Retrieved from http://dx.doi.org/10.3390/su11247016

Kumar, V., Nim, N., & Agarwal, A. (2021). Platform-based mobile payments adoption in emerging and developed countries: Role of country-level heterogeneity and network effects. *Journal of International Business Studies*, *52*(8), 1529-1558. https://doi.org/10.1057/s41267-020-00346-6

Kupfer, A., Ableitner, L., Schöb, S., & Tiefenbeck, V. (2016). Technology adoption vs. continuous usage intention: do decision criteria change when using a technology? *Americas Conference on Information Systems*.

Liao, Y., Wu, W. Y., Le, T. Q., Phung, T. T. T. (2022). The integration of the technology acceptance model and value-based adoption model to study the adoption of e-Learning: The moderating role of e-WOM. *Sustainability, 14*(2):815. Doi: https://doi.org/10.3390/su14020815

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. F. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. *Computers in Human Behavior*, *50*, 186–196. https://doi.org/10.1016/j.chb.2015.03.032

Majumdar, S. R., & Venkataraman, S. (1998). Network effects and the adoption of new technology: evidence from the U.S. telecommunications industry. *Strategic Management Journal*, *19*(11), 1045–1062. https://doi.org/10.1002/(sici)1097-0266(1998110)19:11

Mark-Oliver, K., & Asiedu, E. K. (2010). Challenges of the implementation of E-Learning in Ghana: The Case of Presbyterian University College, Ghana. *ResearchGate*.

Mathivanan, S. K., Jayagopal, P., Ahmed, S., Manivannan, S. S., Kumar, P. J., Raja, K. T., Dharinya, S. S., & Prasad, R. G. (2021). Adoption of e-Learning during lockdown in India. *International Journal of System Assurance Engineering and Management*. https://doi.org/10.1007/s13198-021-01072-4

Matthews, B. and Ross, L. (2010) *Research Methods.* Pearson Longman, London.

McIntyre, D. (2010). In a network industry, does product quality matter? *Journal of Product Innovation Management*, *28*(1), 99–108. https://doi.org/10.1111/j.1540-5885.2010.00783.x

Mohammed Nasser Hassan Ja'ashan, M. (2020). The challenges and prospects of using E-Learning among EFL students in Bisha University. *Arab World English Journal*, *11*(1), 124–137. https://doi.org/10.24093/awej/vol11no1.11

Moreno, V., Cavazotte, F., & Alves, I.E. (2017). Explaining university students' effective use of e-Learning platforms. *Br. J. Educ. Technol., 48*, 995-1009. https://doi.org/10.1111/bjet.12469

Mutisya, D. N., & Makokha, G. L. (2016). Challenges affecting adoption of e-Learning in public universities in Kenya. *E-Learning and digital media, 13*(3–4), 140–157. https://doi.org/10.1177/2042753016672902

Mousa, A. H., Mousa, S. H., Obaid, H. A., (2020). Advance acceptance status model for e-Learning based on university academics and students. *IOP Conference Series: Materials Science and Engineering, 671*(1). https://doi.org/10.1088/1757-899X/671/1/012031

National Academies Press (US). (2015, September 23). *What is trust*. *Trust and confidence at the interfaces of the life sciences and society*. NCBI Bookshelf. https://www.ncbi.nlm.nih.gov/books/NBK321980/

Neuman, W.L. (2014). Experimental Research. In: Neuman, W.L., *Social Research Methods: Qualitative and Quantitative Approaches* (7th Ed.). 281-313. Essex: Pearson.

Ngai, E., Poon, J., & Chan, Y. (2007). Empirical examination of the adoption of WebCT using TAM. *Computers &Amp; Education*, *48*(2), 250–267. https://doi.org/10.1016/j.compedu.2004.11.007

Nguyen, T.D., Nguyen, T.M., Pham, QT., Misra, S. (2014). Acceptance and Use of E-Learning Based on Cloud Computing: The Role of Consumer Innovativeness. In: , *et al.* Computational Science and Its Applications – ICCSA 2014. ICCSA 2014. Lecture Notes in Computer Science, vol 8583. Springer, Cham. https://doi.org/10.1007/978-3-319-09156-3_12

Nielson, B. (n.d.). The difference between a MOOC and an LMS? *LinkedIn.* https://www.linkedin.com/pulse/difference-between-mooc-lms-bryant-nielson/

Nora, A., & Snyder, B. P. (2008). Technology and higher education: The impact of e-Learning approaches on student academic achievement, perceptions and persistence. *Journal of College Student Retention: Research, Theory & Practice*, *10*(1), 3–19. https://doi.org/10.2190/CS.10.1.b

Ouadoud, M., Rida, N., & Chafiq, T. (2021). Overview of e-Learning platforms for teaching and learning. *International Journal of Recent Contributions from Engineering, Science & IT*, *9*(1), 50. https://doi.org/10.3991/ijes.v9i1.21111

Palvia, S., Aeron, P., Gupta, P., Mahapatra, D., Parida, R., Rosner, R., & Sindhi, S. (2018). Online education: worldwide status, challenges, trends, and implications. *Journal of Global Information Technology Management*, *21*(4), 233–241. https://doi.org/10.1080/1097198x.2018.1542262

Pontiggia, A., & Virili, F. (2009). Network effects in technology acceptance: Laboratory experimental evidence. *International Journal of Information Management.* doi: https://doi.org/10.1016/j.ijinfomgt.2009.07.001

Prooijen, A.M.V. (2022). Expert lecture: Methods of Media Research – Survey Characteristics. From: https://canvas.eur.nl/courses/41516/files/68540023?module_item_id=841043

Rawashdeh, A. Z. A., Mohammed, E. a. E., Arab, A. R. A., Alara, M., & Al-Rawashdeh, B. Z. (2021b). Advantages and disadvantages of using e-Learning in university education: Analyzing students' perspectives. *Electronic Journal of e-Learning*, *19*(3), 107–117. https://doi.org/10.34190/ejel.19.3.2168

Ray, A., Ram, S., Lazar, M. & Diaz-Infante, N. (2022). *Demand for online education is growing. Are providers ready?* McKinsey & Company. https://www.mckinsey.com/industries/education/our-insights/demand-for-online-education-is-growing-are-providers-ready

Reddy, N. (2018, January 2). *How To Harness the Power of Network Effects*. Forbes. https://www.forbes.com/sites/forbescoachescouncil/2018/01/02/how-to-harness-the-power-of-network-effects/?sh=5767533262e8

Saleh, S. S., Nat, M., & Aqel, M. J. (2022). Sustainable adoption of e-Learning from the TAM perspective. *Sustainability*, *14*(6), 3690. https://doi.org/10.3390/su14063690

Saloner, G., & Shepard, A. (1995). Adoption of technologies with network effects: An empirical examination of the adoption of automated teller machines. *The RAND Journal of Economics*, *26*(3), 479. https://doi.org/10.2307/2555999

Sampling Methods: Types, Techniques & Best Practices. (2022, February 17). Qualtrics. https://www.qualtrics.com/uk/experience-management/research/sampling-methods/?rid=ip

Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management*, *50*, 286–301. https://doi.org/10.1016/j.ijinfomgt.2019.08.008

Schilling, M. (1999). Winning the standards race: Building installed base and the availability of complementary goods. *European Management Journal, 17*(3), 265-274. https://doi.org/10.1016/S0263-2373(99)00005-5

Shankar, V. and Bayus, B.L. (2004). Network effects and competition: An analysis of the home video game industry. *Strategic Management Journal 24*, 375–384. https://dx.doi.org/10.2139/ssrn.296534

Smallwood, D.E. and Conlisk, J. (1979). Product quality in markets where consumers are imperfectly informed. *Quarterly Journal of Economics 93*(1):1–23. https://doi.org/10.2307/1882595

Song, M., Parry, M. E., & Kawakami, T. (2009). Incorporating network externalities into the Technology Acceptance Model. *Journal of Product Innovation Management*, *26*(3), 291–307. https://doi.org/10.1111/j.1540-5885.2009.00659.x

Statista. (n.d.). *Online Learning Platforms - India | Market Forecast*. https://www.statista.com/outlook/dmo/eservices/online-education/online-Learning-platforms/india

Stecuła, K., & Wolniak, R. (2022). Advantages and disadvantages of E-Learning innovations during COVID-19 pandemic in higher education in Poland. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 159. https://doi.org/10.3390/joitmc8030159

Stobierski, T. (2020, November 12). *What Are Network Effects? | HBS Online*. *Business Insights Blog*. https://online.hbs.edu/blog/post/what-are-network-effects

Stremersch, S., Tellis, G. J., Hans Franses, P., & Binken, J. L. G. (2007). Indirect network effects in new product growth. *Journal of Marketing*, *71*(3), 52–74. https://doi.org/10.1509/jmkg.71.3.052

Stylidis, K., Wickman, C., & Söderberg, R. (2020). Perceived quality of products: a framework and attributes ranking method. *Journal of Engineering Design*, *31*(1), 37–67. https://doi.org/10.1080/09544828.2019.1669769

Sudicky, P., & Zounek, J. (2013). Heads in the cloud: Pros and cons of online learning. *DisCo.* http://dx.doi.org/10.13140/RG.2.2.34075.87840

Suleman, H., Ssekakubo, G., Marsden G. (2011). Issues of adoption: Have e-Learning management systems fulfilled their potential in developing countries? *SAICSIT '11: Proceedings of the South African Institute of Computer Scientists and Information Technologists Conference on Knowledge, Innovation and Leadership in a Diverse, Multidisciplinary Environment,* 231–238. https://doi.org/10.1145/2072221.2072248

Sun, B. (2017). Research on initial trust model of mobile banking users. *The Journal of Risk Analysis and Crisis Response 7*(1):13. http://dx.doi.org/10.2991/jrarc.2017.7.1.2

Tarhini, A., Hone, K., & Liu, X. (2014). The effects of individual differences on e-Learning users' behaviour in developing countries: A structural equation model. *Computers in Human Behaviour*, *41*, 153–163. https://doi.org/10.1016/j.chb.2014.09.020

Tucker, C. (2018). Network effects and market power: what have we learned in the last decade? *Antitrust*, 72-79.

Wang, C., Zhang, Y., & Chen, S. (2021). The empirical study of college students' e-Learning effectiveness and its antecedents toward the COVID-19 epidemic environment. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.573590

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, *31*(6), 572–581. https://doi.org/10.1016/j.ijinfomgt.2011.03.004

Zhang, M. (2021). Assessing two dimensions of interpersonal trust: Other-focused trust and propensity to trust. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.654735

Zhou, J., & Wan, X. (2022). How to build network effects on online platforms for mental health. *California Management Review, 64*(4), 20–46. https://doi.org/10.1177/00081256221107421

Zubair, A. M. (2023). Experimental research design-types & process. *Academia Open.*

Appendix A

Measurement Instrument

Start of Block: Welcome

Introduction Dear respondent,

Welcome!

Thank you for taking the time to participate in my study. I am a student at Erasmus University Rotterdam and would like to invite you to fill out our survey.

This survey will take around 2-5 minutes, your participation is completely voluntary, and you have the right to withdraw your consent or discontinue participation at any time without penalty. Your individual privacy will be maintained in all published and written data resulting from the study.

Please read the following consent: I agree to voluntarily participate in this study. I am free to withdraw at any time, without giving a reason. If my answers are used in scientific publications or are published in any other way, my data will be completely anonymous. My personal data will not be sent to third parties. I will not use your name or other identifying information in this study, you will remain completely anonymous. I understand that I will have access to my individual scores on this or future questionnaires upon request, for the duration of the project.

This study abides by the Netherlands' code of conduct for scientific research, as formulated by the VSNU – association of Universities in the Netherlands (www.vsnu.nl), and the EU standards for privacy and data management.

By clicking 'I agree' below, I state to have read the above statements, and to participate in this study voluntarily. If you have questions about this research, in advance or afterwards, you can contact the responsible researcher, Akul Puri, by email: at akul.puri.ap@student.eur.nl.

Thank you for your participation!

○ I understand the above and agree on participating in this research (1)

End of Block: Welcome

Start of Block: Condition I

Q8 Please look at the advertisement carefully and answer the questions to the best of your capacity.

.

End of Block: Condition I

Start of Block: Condition II

Q29 Please look at the advertisement carefully and answer the following questions.

End of Block: Condition II

Start of Block: Condition III

Q24 Please look at the advertisement carefully and answer the following questions.

End of Block: Condition III

Start of Block: Condition IV

Q34 Please look at the advertisement carefully and answer the following questions.

End of Block: Condition IV

Start of Block: Variables

Adoption Intention Please choose the option you find the most suitable.

	Extremely unlikely (1)	Moderately unlikely (2)	Slightly unlikely (3)	Neither likely nor unlikely (4)	Slightly likely (5)	Moderately likely (6)	Extremely likely (7)
The probability that I would consider buying this course on the platform is (8)	o	o	o	o	o	o	o
The likelihood that I will purchase this course/subscribe to this platform is (9)	o	o	o	o	o	o	o
If I were going to buy an e-platform subscription, the probability of buying this would be (10)	o	o	o	o	o	o	o

Page Break

Initial Trust Please choose the option you find most suitable

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
This platform is trustworthy (1)	○	○	○	○	○	○	○
I trust this platform keeps my best interest in mind (2)	○	○	○	○	○	○	○
This platform will keep the promises it makes to me (3)	○	○	○	○	○	○	○
I believe in the information that this poster provides me (4)	○	○	○	○	○	○	○
This platform wants to be known as the one who keeps promises and commitments (5)	○	○	○	○	○	○	○

Page Break

Perceived IB Please answer the questions to the best of your capacity

	Very Low (1)	Low (2)	Somewhat Low (3)	Neutral (4)	Somewhat high (5)	High (6)	Very High (7)
What's your impression of the number of students enrolled on the platform? (1)	○	○	○	○	○	○	○

Page Break

Complements Please choose the option you find the most suitable

	Very Low (1)	Low (2)	Somewhat Low (3)	Neutral (4)	Somewhat High (5)	High (6)	Very High (7)
What's your impression of the variety of choices that the platform provides? (1)	o	o	o	o	o	o	o
What is your impression of the quality of content on the platform? (4)	o	o	o	o	o	o	o

End of Block: Variables

Start of Block: Trust

Propensity to Trust Please read the statements carefully and choose the most suitable option.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
It is easy for me to trust a person/thing (1)	o	o	o	o	o	o	o
My tendency to trust a person/thing is high (2)	o	o	o	o	o	o	o
I tend to trust a person/thing even though I have little knowledge of it (3)	o	o	o	o	o	o	o
Trusting someone or something is not difficult (4)	o	o	o	o	o	o	o

End of Block: Trust

Start of Block: Block 7

Q43 Any other remarks (optional)

____

End of Block: Block 7

Start of Block: Demographic Questions

Q3 Age (in numbers)

____

Q4 Gender

- ◯ Male (1)
- ◯ Female (2)
- ◯ Non-binary (3)
- ◯ Prefer not to say (4)
- ◯ Other (5) ____

Q5 Nationality

____

Q6 University/Institution

____

End of Block: Demographic Questions

Appendix B

Measures, factor loadings, and Cronbach alphas

Construct	Items	Factor Loadings
Adoption Intention	(α = .93) (1=strongly disagree, 7= strongly agree)	
	1. The probability that I would consider buying this platform is	0.96
	2. The likelihood that I will subscribe to this course/platform is	0.96
	3. If I were going to buy an e-platform subscription, the probability of buying this would be	0.89
Propensity to Trust	(α =.89) (1=strongly disagree, 7= strongly agree)	
	1. It is easy for me to trust a person/thing	0.93
	2. My tendency to trust a person/thing is high	0.92
	3. I tend to trust a person/thing even though I have little knowledge of it	0.86
	4. Trusting someone or something is not difficult	0.75
Initial Trust	(α =.91) (1=strongly disagree, 7= strongly agree)	
	1. The platform will keep the promises it makes to me.	0.92
	2. I believe in the information that this poster provides me	0.90
	3. This platform is trustworthy	0.90
	4. I trust this platform keeps my best interest in mind	0.88
	5. The platform wants to be known as the one who keeps promises and commitments	0.72

Appendix C

Nationality

American	3	2.50
Australian	1	0.80
Belarusian	1	0.80
Belgian	2	1.70
Canadian	1	0.80
Chinese	3	2.50
Costa Rican	1	0.80
Croatian	2	1.70
Danish	1	0.80
Dutch	8	6.70
French	1	0.80
German	4	3.30
Greek	1	0.80
Indian	65	54.20
Indonesian	1	0.80
Italian	1	0.80
Latvian	1	0.80
Malaysian	1	0.80
Mauritian	1	0.80
New Zealand	1	0.80
Polish	2	1.70
Portuguese	2	1.70

Romanian	3	2.50
Serbian	1	0.80
Spanish	4	3.30
Swizz	1	0.80
Syrian	2	1.70
Taiwanese	1	0.80
United States of America	2	1.70
Vietnamese	1	0.80
University/Institution		
Amity University	1	0.80
Ashoka University	25	20.80
Bangalore University	1	0.80
Business School Cologne	1	0.80
Central European University	1	0.80
Delhi University	2	1.70
Drexel University	1	0.80
Erasmus University Rotterdam	42	35.00
Tufts University	7	5.80
Panjab University	5	4.20
Guru Nanak Dev University	2	1.70
Hogeschool Rotterdam	1	0.80
ICAI	1	0.80
IITDM	1	0.80
IIT Kanpur	1	0.80

Instituto Marangoni	1	0.80
Jawaharlal Nehru University	1	0.80
Langara College	1	0.80
Macquarie University	1	0.80
MBO ROC	1	0.80
MMU	1	0.80
NIFT Delhi	1	0.80
NLU Jodhpur	1	0.80
NMIMS	1	0.80
Northern College	1	0.80
Pearl Academy	1	0.80
Panjab Engineering College	1	0.80
Private School	1	0.80
Royal Roads University	1	0.80
SPJIMR	1	0.80
Sophia College	1	0.80
University of Amsterdam	1	0.80
University of Glasgow	1	0.80
University of Guelph	1	0.80
University of Melbourne	1	0.80
University of Michigan	1	0.80
University of Toronto	1	0.80
University of Twente	1	0.80
UPM	1	0.80

Vocational School	1	0.80
Welingkar Institute of Management	1	0.80
Total	120	