Adoption of Learning Innovations within UK Universities:

Validating an Extended and Modified UTAUT Model

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Abstract

Rapid changes affecting the whole world did not spare universities as they face a lot of challenges and pressures. The national and international competition between universities is gaining more momentum. Many universities are experimenting with and adopting different innovative approaches and technologies an attempt to enhance their education and services to secure more students and funds.

The topic of innovation received quite a lot of attention in recent years. Despite the growing attention to innovation in services, however, little attention has been given to innovations and their diffusion in universities.

A number of theories and models were developed and validated in different contexts to help explain the adoption of innovations and technologies. However, such theories and models did not lead to a significantly better understanding of what leads to the adoption and diffusion of innovations within universities.

Based on well-established adoption theories and models, this study proposed a new model that helps explain the adoption of learning innovations within UK universities. Two education-related constructs expected to influence innovation adoption were also developed and tested. Using a quantitative survey approach and utilising a questionnaire instrument, data was collected from staff members from a number of UK universities. Analysis of data showed that the proposed model explains up to 30%, and in some cases more, of the variance in the innovation adoption behaviour of staff members in UK universities. Model testing and development resulted in some interesting new relationships and influences that had not previously reported. For instance, the students' requirements and expectations constructs proposed was found to influence the intention as well as the use of innovations.

Practical recommendations to help UK universities in diffusing innovations are also discussed in detail at the end of this study, which concludes by emphasising the importance of nurturing staff members to encourage and promote innovation in learning.

Abbreviations

HEIs: Higher Education Institutions
ITAMs: Instructional Technology Adoption Models
CBAM: Concerns-based Adoption Model
IDT: Innovation Diffusion Theory
DoI: Diffusion of Innovation
TRA: Theory of Reasoned Action
TPB: Theory of Planned Behaviour
TAM: Technology Acceptance Model
UTAUT: The Unified Theory of Acceptance and Use of Technology
PE: Performance Expectancy
PU: Perceived Usefulness
EE: Effort Expectancy
PEoU: Perceived Ease of Use
SI: Social Influence
FC: Facilitating Conditions
BI: Behavioural Intention
V: Visibility
T: Trialability
SRE: Students' Requirements & Expectations
SL: Students' Learning
SEM: Structural Equation Model/Modeling
MIs: Modification Indices
EFA: Exploratory Factor Analysis
CFA: Confirmatory Factor Analysis
GOF: Goodness-of-fit

Declaration

I hereby declare that this thesis is my own work and it has not been submitted for a degree at another university.

Glossary

The Innovation
An idea, practice, or object that is perceived as new by an individual or other unit of adoption (Rogers, 2003). Technologies (e.g. Smart boards) are also a form of innovation.

Learning Innovations
Innovations that enhance learning. Educational innovations and instructional innovations are also forms of learning innovations as they impact learning.

Adoption
In this context, adoption refers to the use of innovations.

Diffusion
A process that involves communication of innovation (i.e. information about a new idea) among members of a social system over time through certain channels (Rogers, 2003).

Dissemination
A planned activity to increase the speed at which a specific innovation is adopted and wide-spread (Greenhalgh, 2005). This is a specific definition to the innovation adoption context.

1 Introduction

UK universities and universities around the world are facing a lot of issues and challenges as a result of rapid changes. Some of these issues and challenges are impacting staff's ability to improve, develop, and innovate in their teaching approaches.

The aim of this chapter is to provide a rich background to the issues and challenges facing UK universities while discussing their impact on university staff and the university's ability to innovate to stay ahead of national and international competition. The discussion then narrows down to the research problem and the research questions this study aims to answer.

1.1 Issues Facing UK Universities

The United Kingdom's higher education (HE) sector has long faced a number of issues, challenges or difficulties that have affected the way higher education institutions (HEIs) operate. While it is expected that effort and research has been put into the resolution of such problems, some of these problems remain current and perhaps, in some cases, they have developed and become more serious (Withers, 2009). The United Kingdom House of Commons (UK House of Commons, 2009) noted that issues faced by the Robbins Committee and Sir Don Dearing's committee in 1997 remained current, although some had become more complex, and certain circumstances may have changed.

Rapid change affecting the whole world has not spared the higher education (HE) sector in the UK and the increasingly competitive environment has had also had an impact on HEIs.

In this section, the author discusses a number of issues and problems affecting HEIs within the UK. Recent developments that may impact UK universities or threaten their position as leading universities will also be discussed.

1.1.1 Widening Access

Higher education institutions are pressured to provide access to an increasing numbers of students (Neave, 1994; Sorensen, Furst-Bowe, & Moen, 2005) as result of government strategy. In the 1960s, Robbins' report on HE declared the 'Robbins principle' to allow access to higher education for all those qualified to pursue it, and who wish to do so (THES Editorial, 1996), and HE initiatives and its expansion continued.

One of the most noticeable expansions of the HE sector in the UK is the change in status of polytechnics and colleges of higher education into universities, which started in 1992. After the expansion, student numbers continued to rise.

From 1970 to 2007, only a third of a century, the number of students in UK universities increased substantially (more than three times) from 621,000 to 2.4 million (Benton, 2009). In England, students numbers continued to rise from 1.5 million to 1.9 million between 1997 and 2007 (UK House of Commons, 2009). In recent years, statistics show a steady increase in student numbers in the UK in the period from 2000-2011, as can be seen in the following diagram (Higher Education Statistics Agency, 2011).

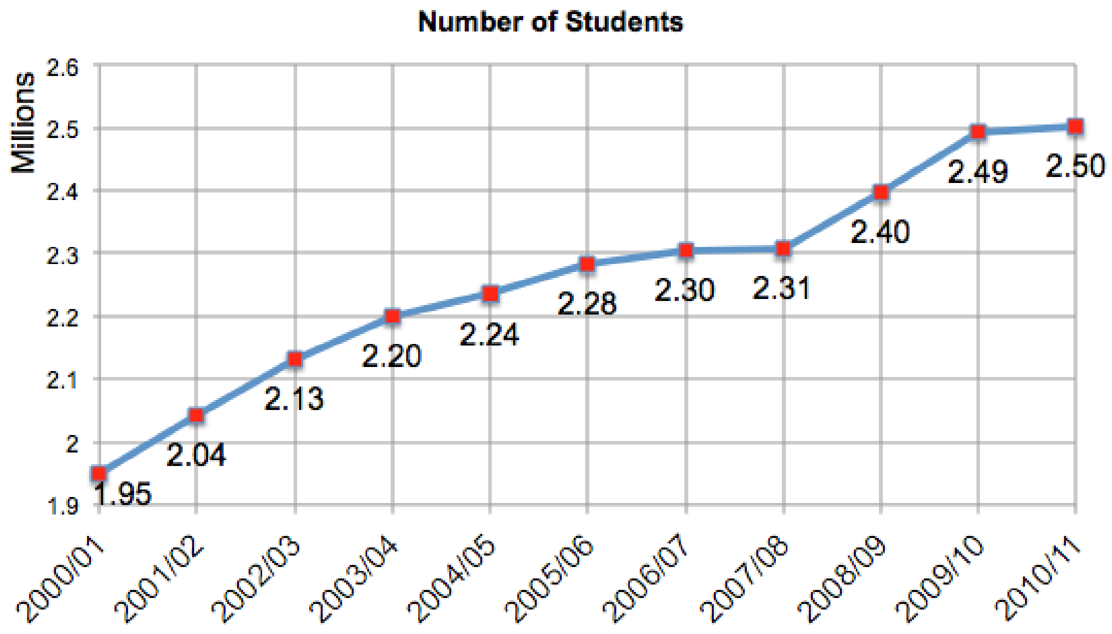

Figure 1.1 Number of Students over the Years

While the government has succeeded in increasing the number of students gaining HE qualifications, a debate has erupted with regard to whether such an increase in numbers has had a negative impact on the quality of the student experience (UK House of Commons, 2009). Furthermore, such increases in student numbers surely require additional resources but it has been noted that while funding should thus have increased proportionately, it has instead been reduced further and further over recent years.

There has been reports of high number of cheating incidents in UK universities (Brady & Dutta, 2012), and while the senior management of some universities may have blamed the financial crisis, in that students were willing to do anything to stay on their degree courses or pass, others have blamed the government's widening access initiatives which, they believe, allowed those without the necessary skills to be accepted into UK universities. If this is true however, does this mean that universities have lowered their standards in order to allow entry to those without the requisite skills? Is this really a direct result of the increase in student numbers, or could it be caused by the lack of additional resources (i.e. money and staff) needed to accommodate such an increase, which may have led to a reduction in the quality of education, leading those students to seek whatever methods they could to pass?

1.1.2 Funding

One of the key challenges facing higher education institutions is budget reduction (Balzer, 2010; Dew, 2007; Sorensen et al., 2005). Despite large increases in students numbers as discussed above, funding has remained low in recent years (Withers, 2009). Benton (2009) reports that there has been a decline in students' funding in the last 20 years.

Faust (2010) in her speech at the Royal Irish Academy noted the financial threat caused by the global recession and that it made things much worse for universities. The recession is, without a doubt, influencing UK universities as well. Faust (2010) also points out the recession caused a number of issues such as faculties cut back, salary reductions, and possibly a decrease in cross-border momentum as universities worry more about national issues rather than growing internationally.

A recent report shown that compared to the allocation of £7,809 million in 2009-10, there was a reduction of approximately 6.5% in the 2010-11 allocated budget of £7,291 million in 2010-11 (UK House of Commons, 2010).

On the national level, the UK seems to be spending less on higher education than the Organisation for Economic Co-operation and Development (OECD) average (Benton, 2009). A more recent report also showed the UK to have the second smallest percentage of budget allocated to higher education, in comparison to other EU countries (European Commision, 2012).

A letter sent from the Department for Business Innovation and Skills to the Higher Education Funding Council in January 2012, entitled Higher Education Funding 2012-13, available on the Gov.uk portal, showed that teaching funds are being cut and will be cut further in the 2013-14 period. This is also the case for research grants.

On this basis, UK universities are challenged to take measures that would help them secure or increase their funding and/or income and to reduce the cost of knowledge creation and dissemination (Hirsch & Weber, 1999).

1.1.3 Reduction in staff/student ratios

As a result of the policy shift in HE in the 1980s which resulted in a large increase in student numbers without a proportional increase in staff, the staff/student ratios dropped severely in Germany, France and Britain (Neave, 1994). Certainly this was to be expected, at least in the UK, since while funding should have been increased to accommodate the various increases in students numbers, it has in fact been reduced further over the years, as seen above.

Lord Dearing stated: “The crisis in 1996 was the result of a period of very fast growth in student numbers, financed in very substantial part by severe reductions in the unit of resource for teaching, and massive decay in research infrastructure” (Crace & Shepherd, 2007) . Statistics show that there was a significant increase in the student/staff ratios, from 8:1 to 20:1 in the period from 1975 to 2004, nearly 150% (Association of University Teachers, 2005). Although there should have been a change or at least an attempt to remedy this problem or to mitigate its affect through the allocation of additional funding, this was not the case.

Up-to-date information with regard to staff/student ratios within individual institutions can be accessed through The Complete University Guide’s League table (The Complete University Guide, 2012). Staff/Student ratios are based on official statistics and reports published by The Higher Education Statistics Agency (HESA). Exploring staff/student ratios in 2012, for a number of institutions, shows that the vast majority of higher education institutions presented in the table had a high staff/student ratio, and many institutions had a staff/student ratio greater than 17:1.

The increase in student numbers through past years and the reduction of budgets have forced HEIs to operate within their current resources, placing greater pressure on staff to do more, while maintaining the quality and cost of the education provided.

1.1.4 Rapid Changing Environment

One of the issues identified in a survey by Weber (Hirsch & Weber, 1999) as a challenge facing HEIs is the changing environment that puts pressure on HEIs and challenges the way they have been used to operating in the past..

Rapid changes affecting the whole world, such as technological, political and economic (e.g. recession) changes, also affecting HEIs (Hirsch & Weber, 1999; Seymour, 1993; Tabata & Johnsrud, 2008). According to Weber, globalisation and the revolution of information technology are perhaps two strong forces at work (Hirsch & Weber, 1999). Similarly, Ketteridge, Marshall, and Fry (2002) attribute the recognition of the importance of knowledge, skills and learning to the fact that countries around the world have become more aware of their rule in driving economic and social development, especially after recent advancements in communication and information technology. Such advancements made it possible to transfer information to a wider audience much more cheaply and quickly (Hirsch & Weber, 1999). Leading universities thus experience both national and international competition, as a result of not being able to continue the monopoly they used to control through dispensing knowledge regionally to students

Students nowadays have access to a wide variety of information online about different courses taught by different universities around the world. In some cases, students participate and graduate from a whole course without having to physically attend any classes. Simply put, students have many more options than in the past. Weber (Hirsch & Weber, 1999) argued that to be globally competitive, decisions about teaching and research can no longer be made without taking into account the specific needs of different types of students, who should be considered as clients.

Coping with such developments requires repositioning of universities and how they operate. Seymour (1993) summarises the need for change: “We are kidding ourselves if we believe that educating people for the year 2000 is essentially the same as educating them for the year 1975. Everything has changed, technology, lifestyle and culture. Our educational institutions must change as well.”

On the other hand, not coping with such demands can render universities incompetent or make them undesirable to their customers (i.e. students) in an increasingly competitive environment where those that excel can, and truly will, strive and be able to secure more funding and expand globally to more markets (e.g. attract students from more countries). This is something that would have been impossible to achieve, had they not changed their traditional ways.

1.1.5 Students Experience

As a result of higher education institutions raising their tuition fees, and students are paying more for their education, student expectations have increased (Department for Business Innovation & Skills, 2010) and will likely to increase further due to international competition and advances in technology and the innovative use of resources for education and learning around the world.

Students are no longer satisfied with the education provided, and employees report a lack in many graduates of the skills required for jobs (Department for Business Innovation & Skills, 2010). One could thus argue that students are paying more and receiving a lesser quality education.

It is no coincidence that the student experience is suffering with the increasing number of students due to wider access, while at the same time, and as explored above, no additional resources have been allocated to accommodate such an increase. Furthermore, with the many issues and challenges facing UK universities, it is no surprise that the Independent Review of Higher Education Funding and Student Finance (Department for Business Innovation & Skills, 2010) report that incentives for universities to improve the student experience are limited.

The need to improve the quality of education and students' experience was also stressed in a more recent report (Modernization of Higher Education Group, 2013).

1.1.6 Demands for Accountability

As a result of increasing tuition fees and demands for accountability (Balzer, 2010; Horine & Hailey, 1995; Seymour & Collett, 1991) higher education institutions are pressured to prove their worth, especially since government agencies, funding bodies, students and their parents want to get good value for their money (Seymour, 1993). According to Sean Coughlan (2011), the UK government says that students have the right to demand value for money if universities continue to charge the maximum tuition fees, however, it is not yet clear whether the increase in tuition fees has been accompanied by an increase in quality (Department for Business Innovation & Skills, 2010).

1.1.7 The impact on HEIs Staffs

Higher education is an industry that relies heavily on the capabilities and wellbeing of its workforce (Kinman, Jones, & Kinman, 2006; National Committee of Inquiry into Higher Education, 1997). Yet, academic staff members are being pressured, over-burdened and stressed.

The Dearing report (1997) pointed out that the role of staff was likely to change in the next 20 years as they undertook different tasks, and that the role of faculty would become more pressured (National Committee of Inquiry into Higher Education, 1997). Certainly with the many challenges facing HEIs nowadays, there is more and more pressure put on staff.

Below, the researcher discusses the impact of the aforementioned challenges and issues on UK universities staff.

1.1.7.1 Increase in Workload

Decreases in staff/student ratios, due to the widening access policy combined with funding cuts, has led to increases in workload and stress for academics. Academic staff within HEIs are experiencing an increase in commitments, especially with larger groups, and are being pressured to research and publish while also having to find time to support students (National Committee of Inquiry into Higher Education, 1997). Davis (2003) similarly noted that lecturers are being “pulled in many directions” as they have to become effective lecturers, successful researchers, and support students, usually with few resources. Demotivated, overburdened and stressed staff are also being pressured to maintain the level and quality of their own work (Brown, Race, & Smith, 1997).

In general, respondents to a number of studies (Kinman et al., 2006; Kinman & Jones, 2003; Lea & Callaghan, 2008) have noted that the demands of their jobs have increased significantly. Similar results were found by studies into stressors in higher education institutions in New Zealand (Boyd & Wylie, 1994; Chalmers, 1998). In New Zealand too, similar to the situation in the UK, staff-student ratios have been deteriorating over the past years.

1.1.7.2 Stress and dissatisfaction

25 per cent of respondents to a survey reported that having too much work with little time was a reason for stress (National Committee of Inquiry into Higher Education, 1997). Another study of almost 800 academics revealed a significant increase in job stress and demands, and a decline in job satisfaction (Kinman & Jones 2003). A number of similar studies into stress were also discussed by the authors. In a follow-up by Kinman et al. (2006), the findings of two studies carried out in 1998 and 2004 were compared. They showed little change in the level of stressors through the six year period, and that high levels of psychological distress found in the 1998 study

remained, and continued to surpass those of similar groups and the population generally. In the same vein, a survey of over 2136 workers working in four UK HEIs showed that, generally, employees were dissatisfied, and reported being stressed at work (Edwards, Van Laar, Easton, & Kinman, 2009). Perhaps being stressed is the root cause of employee dissatisfaction, as it has been associated with job dissatisfaction and a high staff turnover, among other things (Kinman & Jones 2003).

It is not strange to see that stress, psychological distress and job dissatisfaction among other things continue on similar levels compared to previous years, or even escalate further, impacting UK HEIs' staffs as funding is being reduced further.

1.1.7.3 Conflicting Demands

Staffs within UK HEIs are not only being pressured, but some of the pressures they suffer are in conflict, causing more pressure, stress, and affecting how they may perform.

For instance, the pressure to research without a doubt has an impact on the proportion of time lecturers dedicate to teaching activities. On top of that, since larger numbers of students have been allowed to enrol in courses as a result of the widening access policy, activities associated with teaching (e.g. marking and support) require much more time, something the proportionally smaller number of lecturers do not have anymore, which puts more pressure on the lecturers (Lea & Callaghan, 2008).

This increase in workload has led some staff to dedicate much more time to teaching or administration related activities, affecting their research output (Lea & Callaghan, 2008), contrary to the pressure for quality research which has cascaded from HEI to its staff, which in turn, could render the HEI less competitive and impact its ability to secure funding. Respondents to similar studies in New Zealand reported a decline in time spent on activities such as research, publishing and professional development (Boyd & Wylie, 1994; Chalmers, 1998). As mentioned above, New Zealand faces similar issues.

1.1.8 Summary

With the rapid and extreme social, political, economic and technological changes around the world in recent years, it is clear that the curriculum and teaching methods adopted and used in the past are no longer suitable or are out-dated.

Advances in telecommunications and information technologies are accelerating knowledge generation and acquisition (Hefzallah, 1990). Those who believed that computers and communications can be employed to support and help improve education (Dooley, 1999) were indeed correct, as information technologies are giving more power to students and teachers providing them with a wide range of resources, tools and much more.

The free and easy accessibility of information is without a doubt placing a huge pressure on educational institutions to improve, not only because students are able to interact and choose their educational institution of choice between hundreds, if not thousands, of those available on the internet, but in addition, because the availability of the vast amount of information on the internet is threatening the position educational institutions used to hold as the main sources of knowledge. This may possibly lead to the undervaluing of such institutions unless they can prove that what they offer justifies what is paid (e.g. tuition fees, government support, etc.).

Education systems, including HEIs, are facing difficulties in coping with the needs of our rapid changing technological society (Dooley, 1999). Online information sources such as the Khan Academy (over 2700 videos), You Tube, iTunes and many other information sources are generating and sharing the knowledge and experiences of key experts, professionals, educators and others every day, free of charge. Conversely, curriculums taught in many educational institutions around the world remain rigid and are outdated.

There is a clear need for restructuring that involves profound change in how educational institutions function, including a redefinition of teachers' roles and the various players involved in the education process (Dooley, 1999).

Otherwise, some of the traditional approaches and systems used in HEIs for decades may become obsolete in light of new, more innovative and effective ones adopted and used elsewhere (e.g. by competitors).

Universities that are ignoring or are unaware of these changes are likely to lose their position and even perish as students seek more innovative and better alternatives for meeting their always-increasing expectations. When it comes to choices, every country has tens if not hundreds of alternatives. The increase in tuition fees, although it seemed to be an advantageous situation, did not come without its own problems. Students are demanding more value for money, and they have the right to do so.

Based on what was discussed in this section, it is quite a challenge to offer more value for money and stay ahead of the competition (or at least with the competition), while in fact, UK HEIs' staffs are overburdened, stressed and dissatisfied. Some are even quitting their jobs, putting more pressure on the proportionally small number of staffs, affecting their ability to develop and improve what they offer, due to the lack of time and the many conflicting demands. Consequently, the lack of such development impacts directly on students' experiences.

Furthermore, as a result of the way HEIs operate, if for any reason an institution falls behind the competition, more pressure will be placed on the already pressured and stressed staff. This vicious cycle would then continue as the institution becomes even less competitive. The following figure helps illustrate this further.

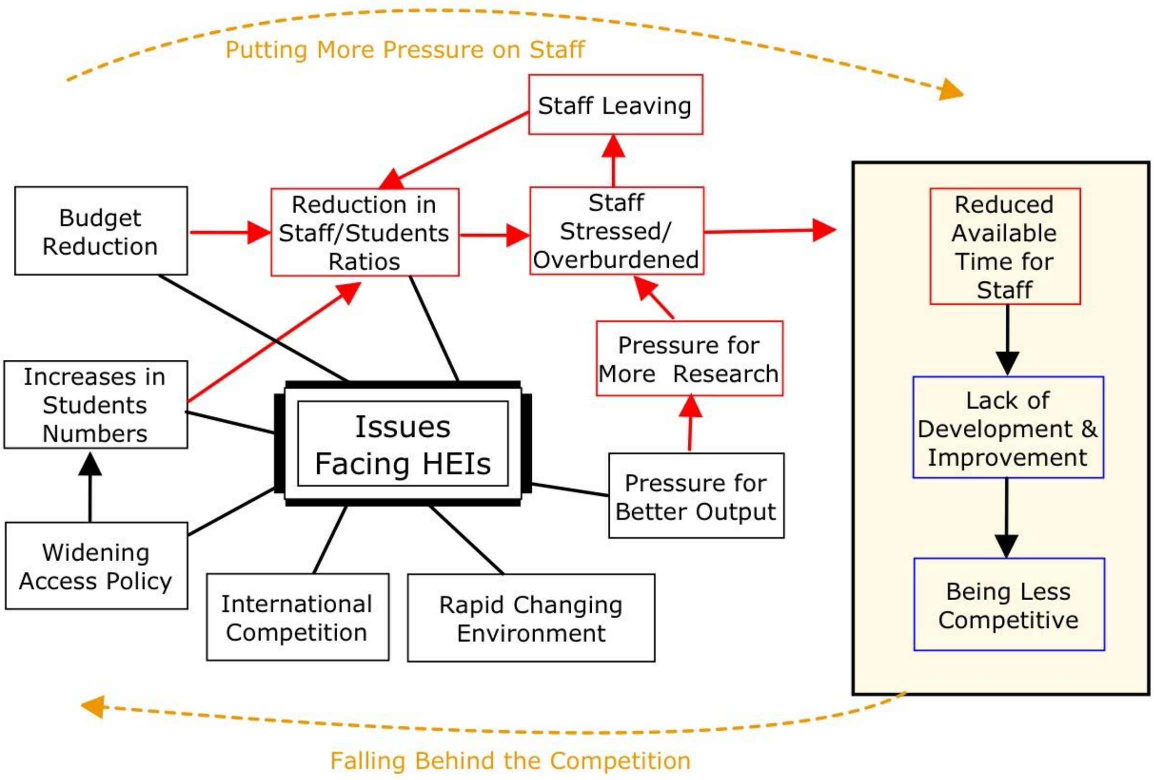

Figure 1.2 Issues and Challenges Facing UK HEIs

HEIs in the UK are facing a lot of challenges nowadays. In order to stay ahead of the competition, they need to continuously think about innovative ways to improve what they offer, to attract more students.

The purpose of this chapter was to clearly demonstrate the difficult situation faced by UK universities and the issues and challenges that are impacting staff members' performance.

Given that universities budget is being reduced further and job demands are increasing significantly, there is a **need for UK universities to be innovative**, to attempt to come up with solutions or ideas that may help improve the current circumstances.

1.2 Research Problem: The Need to be Innovative

Many innovation experts and authorities (Brands & Kleinman, 2010; Christensen, 2011; Dyer, Gregersen, & Christensen, 2011; e.g. Shapiro, 2001) have argued for the need to be continuously innovative to survive and thrive. There is also a need to understand that there are possible risks associated with not innovating and being idle (Christensen, 2011; Von Stamm & Trifilova, 2011). This, however, does not need to be specific and applicable only to the business world, since universities too, need to continuously innovate and improve to stay ahead of the competition and avoid falling behind. Universities do not have the luxury of being idle any more, the issues discussed above and the following help illustrate this further.

Technologies are evolving in this era and the internet continues to expand, reaching more users. Ofcom (2012) reports: "Eight out of 10 people in the UK had access to the internet in the first quarter of 2012". Their extensive report has much interesting information about mobile phones, tablets and internet use, all of which should be carefully studied by universities hoping to take advantage of this revolution. After all, universities, as is the case with other private and public sector organisations, need to stay up to date by adopting or taking advantage of such technologies, otherwise, they may risk being left behind or out-performed by competitors striving to get more funding.

Take one clear example, social networking platforms are nowadays attracting and continuing to attract millions worldwide. Current and next generation students are technology natives: they grew up with these technologies, are used to them, and they expect to continue using them in the future (Withers & Hildyard, 2009). It is therefore likely that students will expect universities to be technologically advanced. Whether universities meet such expectations is their decision (Mayes, Morrison, Mellar, Bullen, & Oliver, 2009). However, it is clear that ignoring such expectations would mean ignoring a large number of customers, who nowadays have too many options to choose from!

One thing that is clear today is that younger people are using new technologies effectively every day, and if educators do not start using them and learning from them, or how best to use them, they might become irrelevant (Kapp, 2006). Prensky (2001) commenting on the difficulties facing education in the US, similarly argues that **one key reason** for the decline in education is the fact that the education system was originality designed for a different type of student and that today's students differ as a result of radical change. The same can be argued for the UK higher education system.

Technologies, nowadays, not only influence how students think and how they learn, but also, how they might think and learn (Owen, 2004; Prensky, 2001). Educators therefore need to understand and exploit the various opportunities offered by technologies in the digital era, especially if they can be used to enhance the quality of teaching and learning (Modernization of Higher Education Group, 2013).

Educational innovations and technologies could help higher education institutions realise a number of benefits, including allowing access to more students, the flexibility of instruction and learning, improving communications, creating effective learning environments, and more (Birch & Sankey, 2008; Lonn & Teasley, 2009; Miller, Martineau, & Clark, 2000; Nachmias & Ram, 2009; Shea, Pickett, & Li, 2005; Surry & Land, 2000; Zemsky & Massy, 2004). Student satisfaction is also of high importance and it should be one of the priorities of universities; it can be met or exceeded with the help of innovative uses of technology to improve learning and teaching (Mayes, Morrison, Mellar, Bullen, & Oliver 2009; Nachmias & Ram, 2009; Modernization of Higher Education Group, 2013).

Widening access policies in UK higher education are allowing more students to benefit from the education system. In this matter, technology, as a key tool to widening access, can help in achieving such a goal by providing distant access to material or even classes (Withers & Hildyard, 2009). Many (e.g. Zemsky & Massy 2004; Shea et al. 2005; Tabata & Johnsrud 2008; Withers & Hildyard 2009) have looked at how technology can be used to teach online or how the internet can be used as a medium for the transfer of knowledge.

In a speech in 2009, the Secretary of State for Innovation, Universities and Skills repeated the claim that there was a chance for the UK to become the global leader in online learning (Denham, 2009). Certainly, online education provides a great opportunity for UK universities not only to promote, market, and establish themselves as leading universities, but also to increase student access to higher education as mandated by HE policies.

Many competing US universities have started various massive open online courses (MOOC) initiatives (e.g. edX and Coursera) attracting many students (i.e. customers). More recently, the European Union (EU) Commission, in its attempts to continuously innovate in higher education, launched its first pan-European university MOOC, aiming to enable further access to free education (European Commision, 2013). While the use of such and other innovations and technologies can certainly help disseminate knowledge or help make it accessible to more, establishing and spreading such initiatives is not an easy task, however.

Providing or enabling the use of innovations (or technologies) is by itself not enough to allow the realisation of all the benefits associated with using them. As noted by Zemsky and Massy (2004), the assumption that the creation of technology would lead to adoption is just wrong. Why? Simply put, no one would benefit from buying the most powerful computer on the planet if it was left untouched! Innovations and technologies which are not adopted (i.e. diffused) would fade away and this would certainly be a bad return on investment.

A considerable amount of time has passed since the beginning of advances in information technology, and in particular, the diffusion and wide-spread use of the internet around the world, in organisations and within houses. Such widespread use of the internet certainly helped in the diffusion of web-based approaches to learning (Rogers, 2003). However, the benefits realised from adopting, integrating, and using technologies to enhance student learning are still slow in arriving, and there has yet to be significant wide-spread improvement in teaching (Lonn & Teasley, 2009; Miller et al., 2000; Nachmias & Ram, 2009; Soffer, Nachmias, & Ram, 2010; Zemsky & Massy, 2004). As Miller et al (2000) put it, technology seems to be least diffused and less common in the classroom. Nowadays, there are personal computers, projectors, and other technologies that are being used, but are these the only innovations that can be used? Is it really possible that today's technology-loving students are learning effectively from the instruction methods that have been used for tens or hundreds of years? This is quite hard to believe. There has to be more appropriate innovative approaches and technologies that can increase the quality of education. However, if such approaches exist, how could they be diffused across departments or universities? Soffer, Nachmias, and Ram (2010) alert us to the fact that if diffusion of innovations within universities happen, it does not necessarily mean that adopted innovations are being used effectively or that they are impacting learning significantly.

Based on the vast literature on the diffusion of innovations, of equal importance with the need to be innovative and make innovations and technologies accessible is the process of actually getting individuals (staff members or students) to adopt and use these innovations or technologies and to understand how and why they may adopt them (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2005; Rogers, 2003); this is not an easy task and it can be very complex (Miller et al., 2000; Nachmias & Ram, 2009), especially with the strong resistance to change taking place within many universities (Moser, 2007).

That being said, the ability to evaluate the success of various technologies and innovations used in universities will likely depend largely on how many and how well adopters (i.e. staff) make it work. Most importantly, therefore, members of staff need to understand and agree to the use of such innovations that enhance learning. Otherwise there will be faculty resistance.

Similarly, if applicable, in case innovations and technologies were offered for their use, students would need to understand how such technologies would enable them to learn prior to deciding whether they should adopt them and use them or not, especially if adoption was not mandated. Otherwise, students' adoption may be less likely (Nachmias & Ram, 2009).

Taking the case of online or distance education as an example, the success of such initiatives is heavily reliant on faculty and/or student engagement and participation (Nachmias & Ram, 2009; Tabata & Johnsrud, 2008). Such engagement and participation will not take place unless a clear understanding of such adoption is gained.

There is a clear need to investigate the adoption of innovations and technologies that would enable UK universities to become global leaders in higher education. A clear understanding of such adoption is a necessity in order to be able to diffuse and encourage the adoption and use of various innovations that may enhance learning. Otherwise, if no such understanding is sought, innovations and technologies adopted may not succeed, their effectiveness may deteriorate, and long-term sustainability is unlikely to happen (Nachmias & Ram, 2009; Zemsky & Massy, 2004), and in a world where technologies are fast progressing, this means falling behind, or at least, losing resources (e.g. time, money, etc.).

Because the ultimate goal of diffusing effective innovations within UK universities requires acceptance and use of innovations by members of staff, the purpose of this research is to investigate attributes or characteristics that influence academic members of staff at UK universities to adopt or reject innovations or technologies that enhance learning. However, as will be explained further in the next chapter, there are no existing models that help explain the adoption of innovations within universities. Therefore, this research will make use of various existing theories and models investigating the acceptance (or adoption) of innovations or technologies that did not originate from this context.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has gained much attention in recent years as it incorporated a number of well-established theories and models into a unified model that was able to explain up to 70% of the adoption behaviour. Therefore, it will be considered as a base model for this study. However, there will be modifications and additions to the model to reflect the need and context of this study. Chapter 2 discusses and compares a number of innovation adoption theories and models while Chapter 3 discusses building the learning innovation adoption model that will be validated in this study.

1.3 The Research Question and Objectives

In order to address the gap in the literature, this study investigates and aims to answer two research questions:

1. How well would a modified Unified Theory of Acceptance and Use of Technology (UTAUT) model explain the adoption of learning innovations within UK universities?
2. Would student requirements and expectations, and students' learning influence the adoption of learning innovations within UK universities?

In order to be able to answer these questions successfully, there are a number of research objectives that need to be achieved:

1. Identify current areas where the UTAUT model is being tested.
2. Investigate other constructs that may help explain the adoption behaviour.
3. Propose and define any additional constructs that may help explain the adoption of learning innovations within UK universities.
4. Define the main hypotheses to be tested.
5. Develop the appropriate research methodology to collect the data.
6. Develop or adapt measures required to test the proposed adoption model.
7. Collect empirical data to test hypotheses and investigate relationships.
8. Test the defined hypotheses.
9. Investigate moderations and mediations to better understand how they may affect the adoption behaviour within UK universities.
10. Based on the literature and the findings of this study, present practical information that can help in encouraging the adoption of learning innovations within UK universities.

1.4 Research Scope: Individuals' Adoption of Innovations

This study is interested in the adoption of innovations by individuals within a university context. Although lecturers within universities operate within an organisation, they do have their own space, in most cases, to innovate and test new ideas or approaches. For instance, some lecturers promote the use of blogs and forums for collaboration or as discussion platforms for their students. Such a decision is usually made by the lecturers.

Bearing in mind that there are attributes or factors that may influence the diffusion of innovation within organisations, the focus in this study is mainly on factors of great value or relevance to the adoption of innovations by individuals. This is mainly because organisational factors come into play when the aim is to promote, diffuse or disseminate innovations within the organisation, which is not directly relevant to an individual thinking about adopting an innovation.

Individual adoption should be observed and studied by organisations so that those innovations proven to be beneficial and effective can then be disseminated across the organisation. To achieve such dissemination, however, end users (e.g. staff) must buy-in. Otherwise, diffusion would not take place. Therefore, this study focuses on understanding adoption from the end user’s perspective, the member of staff who may be thinking about adopting and using an innovation.

Clarifying the focus of this study helps in explaining the direction and attention given to different topics covered.

1.5 Significance of the Study

The higher education industry is very competitive nowadays. Different countries around the world (such as Middle Eastern countries) are investing heavily in knowledge-related initiatives, including providing scholarships to thousands of their students to study abroad. The researcher himself is a beneficiary of such movement. There is therefore a huge opportunity to be realised by UK universities in this and other areas.

To realise this and other benefits, UK universities need to stand out and position themselves as internationally leading universities, otherwise, they will lose a lot of customers.

Students, their parents, as well as governments offering scholarships are targeting top universities, so as to learn from the best and be able to find or create jobs.

This research grew out of the need to understand and encourage further adoption of innovations and technologies that can enhance learning. Quality learning, after all, is what is expected from universities, in addition to their research.

The outcomes of this research will be of great value to different academic groups and those interested in understanding the adoption of innovations in higher education. For instance, this research would be of value to:

- The Department of Business, Innovation, and Skills: in creating (or changing) policies and initiatives to encourage the diffusion of innovations and technologies that have proven to be effective across the sector.
- Those in leadership positions within universities such as administrators, deans, and head of departments: to foster, motivate, reward, and encourage academic members of staff to test and apply various innovations and technologies that can enhance learning; and to create processes or channels for the dissemination of successful experiences or to discuss and improve adopted methods.
- Academic members of staff who are interested in trying various innovations and technologies to improve what they are offering to students. Furthermore,

some may wish to understand what leads to the adoption of such approaches so that they may (if they desire) encourage widespread adoption.

Significant contributions and practical implications resulting from this study are discussed in detail at the end of this study (sections 8.2 and 8.3).

1.6 Thesis Outline

The following is a guide to help the reader navigate throughout the study:

Chapter 2: Innovation Adoption Theories & Models	
Page 24	Innovation adoption theories and models are discussed and limitations and shortcomings are highlighted. The chapter ends with justification for the selection of the UTAUT as a base model to study innovation adoption within UK universities.
Chapter 3: Model Development	
Page 45	Based on the innovation adoption and acceptance theories and models reviewed in the previous chapter, constructs included in the theoretical model proposed by this study are discussed. Additionally, moderating variables are also presented.
Chapter 4: Research Design	
Page 66	After the theoretical model was developed, there is need to collect empirical data to test the model and the various hypotheses proposed by the researcher. This chapter discusses the research approach and data collection instrument used in this study.
Chapter 5: Initial Results & Data Screening	
Page 86	Initial results and demographics are presented. Then, data screening and preparation followed. After that, exploratory and confirmatory factor analyses were carried out to investigate the underlying structure and confirm the reliability and validity of the model.
Chapter 6: Structural Models, Mediations, and Moderations	
Page 142	Based on the measurement model developed in the previous chapter, a hybrid model is developed and hypotheses are tested. Moderation effects are also examined. Additionally, based on recommendations from the software, logical, and some literature indication, a post-hoc model is developed and interesting relationships are examined. Moderation and mediation effects are also examined.
Chapter 7: Data Analysis	
Page 186	Findings of this study are discussed in light of what have been reported by previous studies investigating innovation or technology adoption using one of the theories or models discussed earlier.
Chapter 8: Discussion	
Page 215	The research questions and objectives are re-visited. Contributions to knowledge are highlighted and practical recommendations are discussed. Finally, limitations are discussed and suggestions for future research are presented.
Chapter 9: Conclusion	
Page 252	Key conclusions and findings are summarised and presented in a summary format.

2 Innovation Adoption Theories & Models

Innovation adoption is a complex process that often involves many factors influencing ones' decision to adopt or reject an innovation or technology (Rogers, 2003).

In order to understand what factors may influence the adoption and use of innovations within UK universities, the aim in this chapter is to examine innovation or technology adoption theories and models. To be specific, the researcher aims to investigate which factors were found to influence adoption and whether existing theories and models were used successfully to explain adoption within an education (e.g. university) context. Limitations or shortcomings will also be reported.

One particular research field that have helped advance the understanding of adoption or acceptance is the information systems (IS) field with models originating from or adapted to the field such as the Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTUAT). These continue to attract a lot of attention until today.

In addition to these theories and models mentioned above which aim to explain adoption while usually attempting to validate theories through quantitative means, it is worth mentioning that there are also other frameworks, approaches, and methodologies that could be used by researchers to tackle issues, understand the organisation, and attempt to cause change (e.g. innovation adoption) such as actor-network theory and soft systems methodology. However, because of the lack of use of such approaches in understanding innovation adoption, this study will make use of the well-established and widely used theories and models mentioned above.

Based on the literature review carried out in this chapter and the comparison of the various theories or models, the researcher's decision to use the UTAUT as the base model will be justified and presented at the end of this chapter. However, this does not mean that constructs investigated in the other theories and models will not be considered as well. Further discussion of the constructs and the model development will take place in the next chapter.

The objectives of this literature review are as follows:

1. Investigate theories or models that help in understanding adoption or acceptance of innovations.
2. Examine limitations or shortcoming and areas of application of these theories and models.
3. Clearly justify the selection of the UTAUT as the main base model used by this study.
4. Making use of various factors tested by previous theories and models to extend the theoretical model proposed by this study.

2.1 Innovation Adoption

Although innovation adoption is often treated as an event, early studies demonstrated that usually, it is a long process consisting of a number of steps (Greenhalgh et al., 2005). Many early studies in the diffusion literature have been concerned with and studied the innovation adoption behaviour (Li & Sui, 2011). As a result of these early studies into innovation adoption, it was clear that the decision to adopt (or reject) an innovation is a process involving many factors.

Prior to investigating these attributes and the innovation decision process, it is important to remind the reader of the area of interest (scope) of this study, discussed earlier (1.4 Research Scope: Individuals' Adoption of Innovations).

2.1.1 Innovation-decision process for individuals

The following is a discussion of the innovation-decision process individuals go through as demonstrated first by Ryan and Gross (1943) and later discussed by Rogers (2003) and Greenhalgh et al. (2005).

Figure 2.1 The Innovation Decision Process

Knowledge is gained when an individual learns of the existence of an innovation, while gaining some understanding of how it functions. The adopter at this early stage mainly seeks information, and is more interested in the innovation, how it works, and what benefits of outcomes may result from its adoption. Perhaps of particular importance at this early stage is increasing familiarity with the innovation and reducing the uncertainty or risks associated with its adoption. Mass media is of great benefit as it can be utilised to spread awareness of the innovation.

Persuasion takes place when an individual forms an attitude towards the innovation in question, be it favourable or unfavourable. At this stage, the individual seeks innovation-evaluation information and what advantages or disadvantages may result for their particular situation. Inter-personal relationships and word of mouth are effective at this stage of the process to help persuade potential adopters.

A decision takes place when an individual engages in activities leading to the choice of adopting or rejecting the innovation.

Implementation takes place when the innovation is put into use by the individual. Reinvention may occur at this stage when the adopter decides to change the innovation to suit their needs.

Finally, confirmation is when an adopting individual looks for reinforcement of an innovation-decision which they have already made. If the individual is exposed to conflicting messages about the innovation, the previous decision may be reversed. The individual may reject the innovation because they are dissatisfied with it, or, because the innovation was replaced with something better, which is called discontinuance. Little is known about discontinuance or rejection of innovations as a result of certain biases in the innovation diffusion literature, such as focusing mainly on understanding adoption but not rejection or discontinuance.

2.2 Instructional Technology Adoption Models (ITAMs)

Instructional technology adoption models are models that hoped to explain the adoption process within educational organisations.

While researching theories and model that investigate and explain individuals' adoption behaviour within universities or similar educational organisations, unfortunately, the researcher quickly became aware of the little attention given to this topic.

In this section, the author will briefly discuss two instructional technology adoption models.

2.2.1 Concerns-based Adoption model (CBAM)

The Concerns Based Adoption Model (CBAM) is a model that describes the process individuals progress through as they learn about a certain innovation (Hall & Hord, 1987). CBAM is a high level conceptual framework providing a set of tools and techniques that help facilitate reform in an educational environment. It is primarily concerned with top-down change, as it looks at it from a process perspective consisting of a number of steps.

CBAM assumes that an innovation will be adopted (Hall, Wallace, & Dossett, 1973), and therefore it does not explain the reasons behind innovation adoption, rather, how the assumed adoption can be facilitated once concerns are understood (Straub, 2009). Hall et al. (1973) note the difference in the use of the term 'adoption' in their model to that used by Rogers to indicate the process of deciding to adopt and use a certain innovation. In their case, the term 'adoption' is used to indicate the broad effort of integrating an innovation into an organisation's functional structure.

CBAM introduced seven stages of concerns reflecting people's reactions, feelings, or attitudes towards a new innovation or practice. They start with the individual knowing nothing about the innovation and end with the individual's intent to explore a new or better method than that which they adopted.

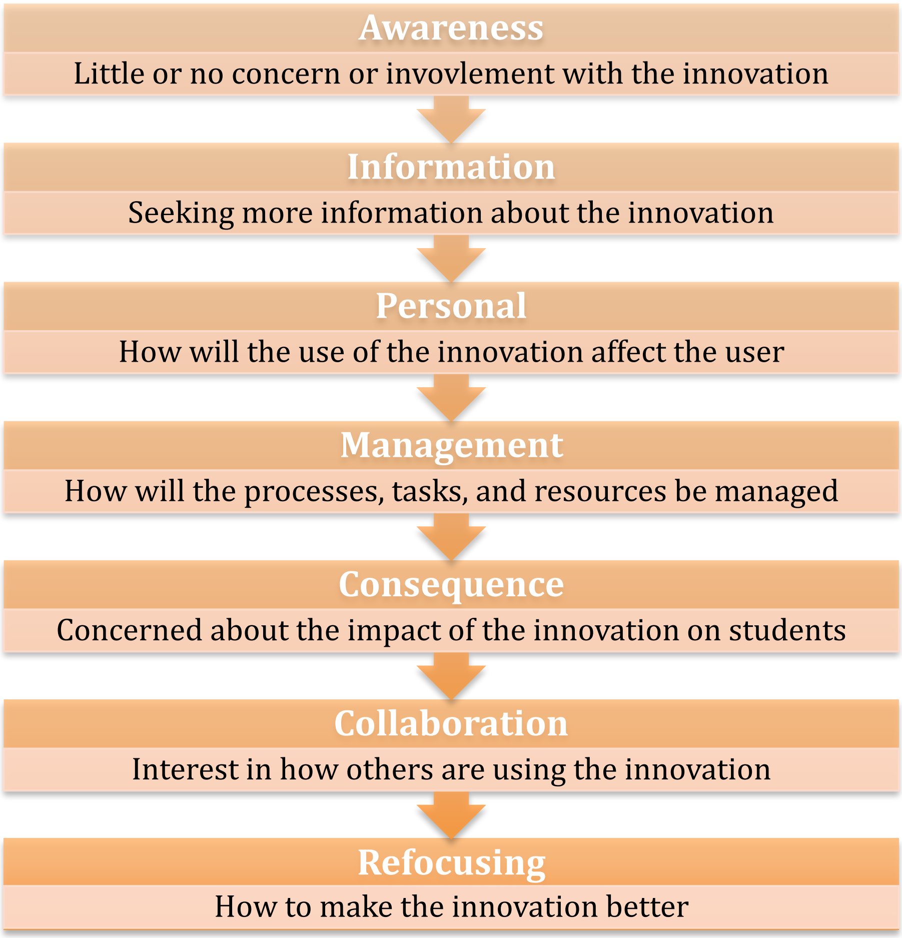

Figure 2.2 CBAM Stages of Concerns

Contrary to the goal of this research, which is to understand what drive the adoption of learning innovations, one key shortcoming in CBAM is its assumption that an innovation will be adopted. As a result it mainly focuses on how to facilitate the diffusion of an innovation that will certainly be adopted. This is not the case with all innovations and the vast majority of research into innovation and technology adoption proves that adoption is never a given.

Another assumption in CBAM is that organisations are fully aware of their current resources, what their needs are, and what specific innovations they will adopt to resolve any problems or remedy these needs (Hall et al., 1973). While this can certainly be the case in some organisations, the fact that the UK higher education system and the instruction methods has mostly stayed the same for too long says otherwise. The discussion of issues facing UK universities earlier in this research, and the fact that many of these issues remain current, impacting staff for too long, demonstrates that organisations are not necessarily always aware of their resources, problems, or needs and how to remedy them.

In the same vein, Straub (2009) discussed the limitations of CBAM. One notable shortcoming noted is a focus on the top-down approach and the reform or change being generally mandatory. A second notable limitation is the disregard of teachers' positive or favourable perceptions of the innovation. Teachers are thus portrayed as always being resistant to change. A third notable shortcoming is the focus on the change agent who is facilitating the reform or change, rather than the teacher who will be the individual adopting and using the innovation.

The aim of this research is to study individuals' adoption of innovation within universities. Adoption of innovations within universities is not always mandated or certain. The study also focuses on the adoption of learning innovations and possible reasons behind it, and not with the process of change or how the innovation can be diffused within an organisation. Meaning, the aim is to understand the adoption behaviour itself rather than how if such behaviour was assumed to diffuse it further. Therefore, CBAM is not considered as a suitable base for the theoretical model that will be developed in this research.

2.2.2 The Learning/Adoption Trajectory Model

One of the models found in the literature is the Integrated Technology Adoption and Diffusion Model. The model describes a learning and adoption cycle that was developed based on Rogers's diffusion of innovation theory and CBAM (Sherry, Billig, Tavalin, & Gibson, 2000). Similar to Roger's innovation-decision process, the model is concerned with the adopter's (in this case the teacher's) progress and development through the innovation-decision cycle as they gain more knowledge about the innovation. The authors offer great recommendations for possible strategies that can be used at different stages to help develop teachers and help them move on to the next stage.

Sahin (2005), in his case study, used the model to understand a faculty member's technology adoption. He provides and discusses several recommendations that can be taken into consideration to progress and reach a later stage of the cycle suggested by the model.

Despite its usefulness in explaining the different stages the teacher or adopter goes through in the innovation-decision process, the model was not developed within the higher education context, although it has been applied to help in the analysis of instructional technology adoption in higher education, and was able to explain approximately 75% of the variance in technology adoption (Sahin & Thompson, 2007). However, as is the case with the previous model, the literature lacks further research validating and supporting the use of the model.

2.3 Innovation and Technology Diffusion (Adoption) Models

There are a number of factors that affect innovation adoption. One important aspect of innovation diffusion is the understanding of the adoption of innovations and the reasons behind such adoption; since increasing the adoption of a certain innovation is likely to help diffuse it further. Put simply, it is very hard or even impossible, to diffuse an innovation within any organisation unless there is adoption from users.

Beyond Rogers' identification of factors affecting adoption, other constructs possibly affecting innovation adoption have been studied by others. Most notable is the work carried out by Davis (1989) and his development of the Technology acceptance model (TAM) which is still being used today to explain technology or innovation adoption. The following is an examination of the models and theories that are considered key to the technology or innovation adoption literature. Many of these theories and models originated from or were used within the information systems (IS) context but were then extended, modified, and/or applied elsewhere.

2.3.1 Innovation Diffusion Theory (IDT)

Rogers's innovation diffusion theory (IDT) has been used since its emergent in the 1960s. The theory helps describe different studies on innovation diffusion ranging from agricultural studies to information systems (Moore & Benbasat, 1991; Rogers, 2003; Greenhalgh et al., 2005). It has been developed and improved over the years.

Based on his extensive review of the literature, Rogers identified five attributes of innovations influencing adoption that were consistent through his examination of a variety of diffusion studies. These attributes are:

- **Relative advantage:** An innovation will only be adopted if it surpasses what it supersedes. While there is strong evidence supporting this characteristic, it does not guarantee wide-spread adoption by itself.
- **Compatibility:** innovations that are well-suited to an individual's values, norms, beliefs and needs are adopted more rapidly.

- **Complexity:** Innovations that seem easy to use have a better chance of being adopted. Moreover, innovations broken into smaller parts, that are adopted incrementally, have a better chance of being adopted.
- **Observability:** If the benefits of a particular innovation are visible and easily recognised, adoption of the innovation will be easier.
- **Trialability:** Innovations which can be experimented with or tested by potential adopters are more likely to be adopted and assimilated. For instance, in one of the most classic diffusion of innovation cases in rural sociology, Iowa farmers tested the new innovation (hybrid corn) by planting it in some of their fields.

In the latest edition of his book, Rogers notes that many innovations were re-invented or changed to suit the situation of the adopter. He argues that an innovation is more likely to be adopted if it can be re-invented.

- **Reinvention:** Closely related to the compatibility of the innovation is the concept of reinvention. If an innovation can be adopted, changed, modified or improved to suit individual circumstances or needs, then the innovation will be adopted more easily.

Tornatzky and Klein (1982) reported additional innovation characteristics that influence adoption, some of which are mentioned above. Others, some of which may be very similar to those reported above, include:

- **Cost:** The cost of a certain innovation.
- **Profitability:** The profit gained from adopting a certain innovation.
- **Divisibility:** The degree to which the innovation can be tested on a small scale prior to adoption.
- **Social approval:** The status gained as a result of the adoption of the innovation.

2.3.2 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) was developed by Ajzen and Fishbein in 1980 to examine the relationship between attitudes and behaviours. It was designed to describe and clarify human behaviours (Ajzen & Fishbein, 1980).

The model aims to study and help predict a single behaviour which involves no choice, although it has been found that the presence of choice did not weaken the predictability of the model (Sheppard, Hartwick, & Warshaw, 1988).

TRA is a very influential theory of human behaviour which has been used to predict different behaviours within different contexts such as marketing, sociology and information technologies (Agarwal, 2000; Venkatesh, Morris, Davis, & Davis, 2003). The extensive Meta-Analysis of 87 studies carried out by Sheppard et al. (1988) provide strong support for the TRA's predictability.

The theory argues that an individual's actual behaviour is determined by their intention to perform that behaviour. The theory has two determinants of behavioural intention (BI), attitude toward behaviour and subjective norms associated with performing the actual behaviour.

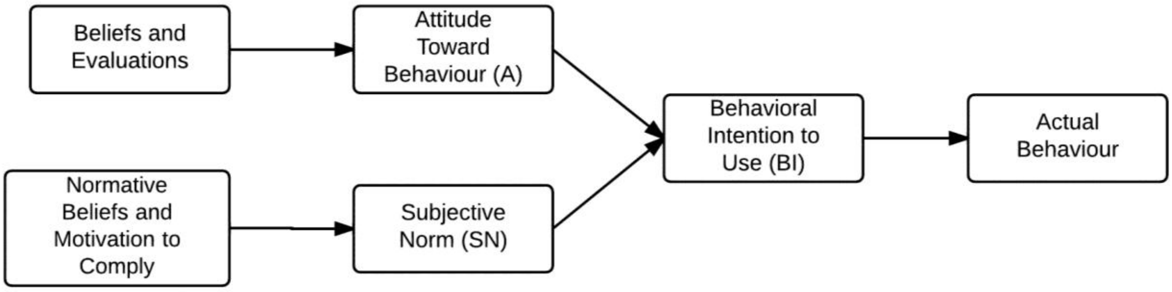

Figure 2.3 The Theory of Reasoned Action (TRA)

2.3.3 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) was introduced by Ajzen as a proposed extension or addition to the TRA theory mentioned above in 1985. In this theory, Ajzen introduced a third independent determinant of the behavioural intention called 'perceived behaviour control', to overcome TRA's weakness with regard to neglecting social factors and their possible influence. Similar to the TRA, TPB is formalised to explain a broad range of individual behaviours (Agarwal, 2000). TPB was adopted and used by different studies to predict intention and behaviour in different settings (Ajzen, 1991).

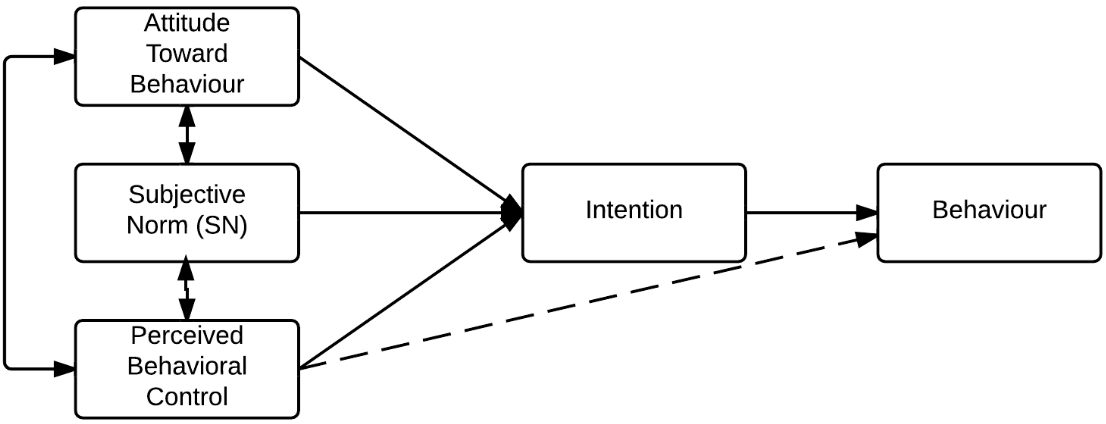

Figure 2.4 Theory of Planned Behaviour (TPB)

2.3.4 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a model that was developed by Davis in 1989. The model was adapted from the previously mentioned TRA to the information systems field. The main purpose of the model was to help explain the determinants of computer acceptance, but, this was expanded to the determination of behaviour for a wide range of technologies across different populations (Davis, 1989).

Unlike TRA, the subjective norm construct was not included in the TAM as a determinant of intentions. Moreover, unlike the TRA, which is considered very general, and "designed to explain virtually any human behavior" (Ajzen & Fishbein, 1980), the TAM is much less general as it is designed for application to computer use (Davis, Bagozzi, & Warshaw, 1989).

TAM speculates that perceived usefulness and perceived ease of use both help determine an individual's behavioural intention to use a system (Venkatesh & Davis, 2000).

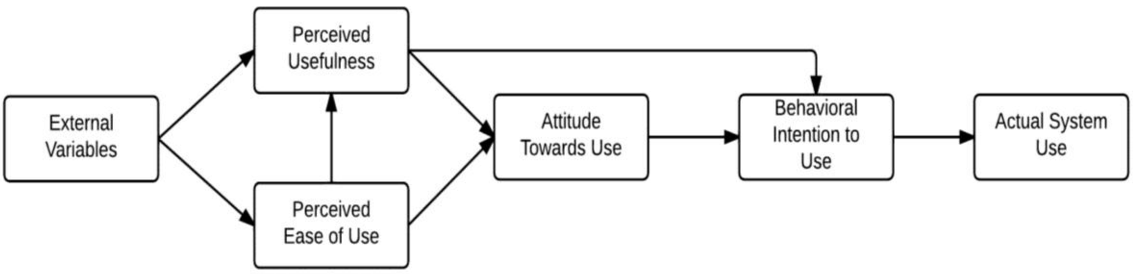

Figure 2.5 Technology Acceptance Model (TAM)

TAM is a strongly-established, well-tested and robust model that helps to predict technology acceptance by users (Venkatesh & Davis, 2000). It has been tested and validated for users with different levels of experiences, and different systems such as: word processing, spread sheet, email, voice mail, e-commerce, web-enabled services, etc. (Carter & Bélanger, 2005; King & He, 2006; Lin & Lu, 2000; Schepers & Wetzels, 2007). TAM has been proven to be successful in predicting more than 40% and up to 70% of technology use (Plouffe, Hulland, & Vandenbosch, 2001; Venkatesh et al., 2003).

In the education, learning, or higher education setting, TAM was also used by a number of studies (Kumar, Rose, & D'Silva, 2008; Lee, Cheung, & Chen, 2005; Liu, Liao, & Peng, 2005; Martins & Kellermanns, 2004; Park, 2009; Saadé, Nebebe, & Tan, 2007; Selim, 2003; Straub, 2009). For instance, TAM was used by Martins and Kellermanns (2004) to study students' acceptance of a web based course management system. In this study, a number of proposed constructs derived from the change implementation and management education literature were validated and shown to be related to both the perceived usefulness and perceived ease of use of constructs within the TAM. However, the whole model was only able to explain a very low 15% of system use.

Venkatesh and Davis (2000) proposed an extension of TAM which they called TAM2. In their study of four different systems at four organisations (n:156), they studied additional constructs: subjective norms, voluntariness, image, job relevance, output quality, and result demonstrability, and their influence on user acceptance. According to the authors, this extension accounted for 40%-60% of the variance in usefulness and 34%-52% of the variance in intention to use. Despite these results, compared to TAM, there is still a need to validate TAM2 in different contexts, and certainly with a larger sample.

Despite its wide applicability and use in the literature, TAM has been criticised. First, there is a flaw in the idea that perceived ease of use can be mapped directly to the self-efficacy concept. Perceived ease of use is concerned with technology while self-efficacy is concerned with an individual's abilities (Straub, 2009). A study by Venkatesh (2000) suggested that these two constructs are conceptually different. Moreover, there are some inconsistencies in the results reported in the literature (King & He, 2006).

Another critique of the TAM is its lack of appreciation of individual differences and how they may affect adoption (Agarwal & Prasad, 1999). The beliefs and attitudes towards adoption of a certain technology are certainly influenced by more than just the two proposed constructs of perceived usefulness and perceived ease of use (Straub, 2009).

Despite being used by a number of studies in the educational context, TAM is unable to capture influences that are likely to be key within the educational setting. For instance, social influence (which was added later in TAM2) will likely to have a strong influence on an individual's decision to adopt an innovation. Members of staff will be concerned with what their peers think of them or how they would perceive their adoption and use of a certain innovation. Other factors and/or conditions within the educational setting may also influence individuals' decisions. For example, students' learning and students' requirements are likely to be two important factors in the educational setting which cannot be captured directly by TAM or TAM2.

2.3.5 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model that is based on constructs of eight established models including the aforementioned TRA, TBP, IDT, TAM and other theories or models such as the Motivational model, the combined TAM-TPB, model of PC Utilisation, and the Social Cognitive Theory (Venkatesh et al., 2003).

The UTAUT was created to help address some of the shortcomings of the TAM model, such as TAM's exclusion of possible important constraints such as required resources (e.g. time and money) that would influence an individual's decision or prevent them from adopting an information system.

The UTAUT model was tested by Venkatesh et al. (2003) in different organisational settings. It accounted for 70 per cent of the variance (R2) in intention to use which is considered to be a substantial improvement over previous models (Venkatesh et al., 2003). Additionally, the UTUAT looked at and tested the influence of moderating factors, some of which received little attention in the technology adoption literature but proved to be significant. The UTAUT is thus considered the best model, allowing for a better understanding of technology acceptance (Jong & Wang, 2009).

A number of studies adopted and tested the UTUAT model in different contexts. Gogus, Nistor, and Lerche (2012) tested the applicability of the UTUAT to study educational technology users in a Turkish culture, noting that the model has yet to be tested in many cultures. Additionally, they found that the intention-behaviour correlation suggested by the UTAUT and other models to be extremely low, calling for alternative explanation. Others have used the UTAUT to understand technology adoption in education (e.g. El-Gayar & Moran 2006; Jong & Wang 2009).

Oshlyansky, Cairns, and Thimbleby (2007) validated the use of the model across different cultures, concluding that the UTAUT model is adequately robust and that it can be used outside of its original country and in other languages.

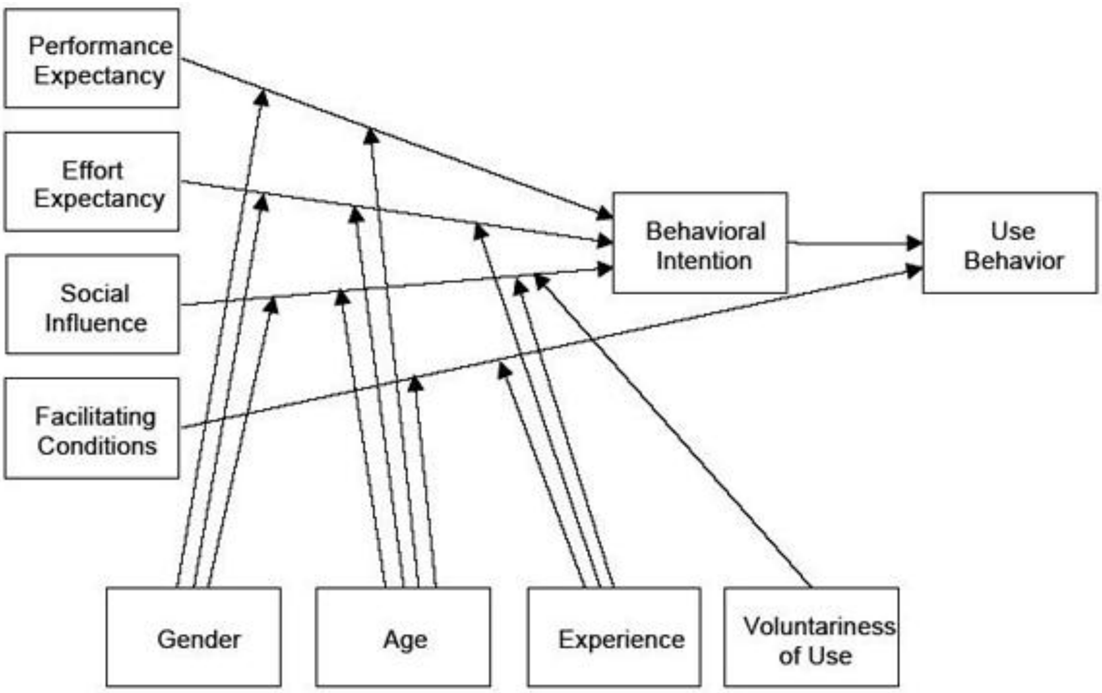

Figure 2.6 The Unified Theory of Acceptance and Use of Technology (UTAUT)

Compared to the TAM and many of the other models or theories (e.g. IDT, TRA, TPB), the UTUAT's consideration of constraints that may influence adoption is very important, especially in the context of UK universities, as it is very likely that those constraints play a major role in predicting the adoption and use of learning innovations as a result of issues and challenges faced by these institutions and the lack of resources.

Although many studies validated the UTAUT model, there are a number of limitations with regard to the contexts and the sample selection.

As far as the researcher is aware, to date, validation of the UTAUT within an education (or higher education) sector has only been performed outside the United Kingdom (Gogus et al., 2012; Jong & Wang, 2009; Marques et al., 2011; Oye, A.Iahad, & Ab.Rahim, 2012b; Yamin & Lee, 2010). Additionally, many studies (e.g. El-Gayar & Moran, 2006; Jong & Wang, 2009; Sumak, Polancic, & Hericko, 2010; Yamin & Lee 2010; Hsu 2012; Lakhal, Khechine, & Pascot, 2013) used students as participants, and although this has also been the case when testing similar previous models (e.g. TAM), students are different from members of staff (e.g. in autonomy, responsibilities, work pressure).

The researcher found no studies that attempted to investigate the adoption of different multiple innovations or technologies within UK universities. The norm is to test the UTAUT or similar models to predict the adoption and use of a single technology, such as an e-mail client, e-learning system, and so on.

Although the UTAUT is considered a robust model that can help in understanding innovation adoption in UK universities, it is clear that the model was not originally developed to be tested in an educational context without any modifications or extensions. For instance, the model does not cover educational-specific factors such as students' requirements and expectations and students' learning, even though they are crucial. Therefore, testing the UTAUT by itself will therefore not help capture information that will likely be important when studying innovation adoption in universities. Further details about both factors and their importance are covered in the next chapter (section 3.1.3 Education Constructs).

Finally, the UTAUT fails to test or capture other important constructs such as reinvention, results demonstrability, and trialability, all of which have strong support in the innovation literature (Karahanna, Straub, & Chervany, 1999; Moore & Benbasat, 1991; Odumeru, 2013; Rogers, 2003; Suoranta, 2003; Wejnert, 2002).

2.4 Summary

The purpose of this chapter was to briefly discuss the innovation adoption process, and then, to research and investigate a number of technology adoption theories and models. A number of key innovation diffusion and adoption theories and models were explored. These included instructional technology adoption theories and models developed specifically for the education context as well as innovation and technology acceptance and use theories and models.

In the following table, the author presents a brief summary of what was discussed in this chapter while highlighting some of the key advantages (green) and disadvantages (red) of each theory or model.

Theory/Model	Brief	Notes
Concerns-based Adoption model (CBAM)	A process for facilitating change within an educational context.	• Assumes that adoption is a given. • Assumes that the organisations are aware of its resources, problems, needs, and how to solve them. • Follows a top-down approach rather than aiming to understand adoption from the user's perspective. • Not clear what factors influence the adoption and diffusion of innovations. • Rare mention and support in the literature. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption.
The Learning/Adoption Trajectory Model	Concerned with the adopter's progress and development through the innovation-decision cycle as they gain more knowledge about the innovation.	• Not clear what factors influence the adoption and diffusion of innovations. • Rare mention and support in the literature. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption.

Innovation Diffusion Theory (IDT)	Based on extensive literature survey, the theory Identified key attributes of innovations influencing adoption.	• Influenced many of the innovation adoption theories and models. • No attention given to students related factors that may influence adoption.
Theory of Reasoned Action (TRA)	Examines the relationship between attitudes and behaviours. Argues that an individual's actual behaviour is determined by their intention to perform that behaviour.	• Influenced many of the innovation adoption theories and models (the intention-behaviour link specifically). • Neglected social related influences. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption.
Theory of Planned Behaviour (TPB)	Suggested adding 'perceived behaviour control', to overcome TRA's weakness with regard to neglecting social factors and their possible influence.	• Influenced many of the innovation adoption theories and models. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption.
Technology Acceptance Model (TAM)	Adapted from the TRA to the information systems field to help explain adoption of information systems.	• Influenced many of the innovation adoption theories and models. • One of the most used theories to explain adoption as it has been validated and used to explain adoption within many different contexts. • Successful in predicting more than 40% and up to 70% of technology use. • Neglected social related influences. • A flaw in the idea that perceived ease of use can be mapped directly to the self-efficacy. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption.
The Unified Theory of Acceptance and Use of Technology (UTAUT)	A model that is based on constructs of eight established models including the aforementioned TRA, TBP, IDT, TAM	• A global model that Incorporated and built on many of the factors that were used and tested in previous well-established theories and models. • Successful in predicting up to 70%

	and other theories or models.	of the variance in the intention to use. • Investigated mediation and moderation effects to highlight their possible influence on adoption. • The model was not developed within the higher education context. • No attention given to students related factors that may influence adoption. • Failed to capture some other important constructs that were investigated by previous studies such as reinvention, results demonstrability, and trialability.

Table 2.1 A brief comparison of the investigated theories and models

Upon investigation of two instructional technology adoption theories and models (CBAM and the Learning/Adoption Trajectory Model), these were quickly regarded as insufficient for understanding what leads to adoption within UK universities. It was found that CBAM assumes that adoption will happen while the Learning/Adoption Trajectory Model had little existence in the literature and did not look at attributes that may influence adoption or use but rather at how the adopter proceeds from one stage to the next in the adoption process. Furthermore, both of these approaches did not look at or study how students' related factors such as students' learning would influence the adoption.

Next, a number of innovation and technology adoption or acceptance theories and models were discussed. Theories and models discussed had a vast supporting literature where other researchers attempted to validate, extend, and test these theories and models within different contexts. Moreover, most of them were able to explain a good part of the variance in the adoption or acceptance behaviour. In addition to discussing and showing support for these theories and models, limitations and shortcomings were also discussed.

In the next chapter and based on the literature review, the innovation adoption model will be constructed. The Unified Theory of Acceptance and Use of Technology (UTAUT) is considered the base theoretical model by this study. This choice was attributable to the fact that the UTAUT is a global model that integrates established models and theories explaining technology adoption or acceptance (Ajzen 1991; Compeau & Higgins 1995; Davis 1989; Moore & Benbasat 1991; Thompson et al. 1991; Fishbein & Ajzen 1975). Moreover, the UTAUT was able to explain the adoption or acceptance of technologies better (70% of variance explained) than other technology acceptance or adoption theories and models.

Despite their previous inclusion and testing in the UTAUT, the study will also attempt to include and retest some of the constructs proposed by Moore and Benbasat (1991) which may have been dropped from the UTAUT.

Both of the aforementioned model and theory will serve as a theoretical base for the UK universities innovation adoption model proposed by this study. Further discussion about the integration and the proposed model is covered in the next chapter.

3 Innovation Adoption Model Development

In the previous chapter, the researcher discussed a number of established innovation adoption models that were tested and validated within different contexts.

This chapter builds on what has been discussed previously in order to develop the learning innovations adoption model that will be validated within the UK universities in subsequent parts of this study.

Venkatesh et al. (2003) reiterated the need to test the model in different contexts. Similarly, Straub (2009) stated the essential need for further validation of the UTAUT model since it is relatively new and has not yet been thoroughly tested from an education perspective. Despite the existence of more recent studies as discussed previously (2.3.5 above), this still stands because most studies that aimed to validate the UTAUT within an education context have used small samples and/or students. While using students to understand adoption from their perspective is useful, they are not considered similar to members of staff especially if there was a need to understand adoption from members of staff's perspective.

The research model used in this thesis to help understand innovation adoption in UK universities will be based on the UTAUT model (Venkatesh et al., 2003) as well as the diffusion of innovation theory (Moore & Benbasat, 1991; Rogers, 2003), in addition to two proposed constructs related to the education context.

When it comes to the technology or innovation in question, it has been the norm that studies on technology acceptance capture information related to a single technology or innovation. Schepers and Wetzels (2007) in their meta-analysis of different studies related to technology acceptance concluded that the technology under consideration had a significant moderating effect on the constructs used in TAM.

Moreover, Tornatzky and Klein (1982) recommended researchers to look at multiple innovation characteristics within the same study, as this would allow for evaluation of and a better understanding of the different characteristics, their relative predictive power, and any inter-relationships between them.

Taking both recommendations into consideration, this study will investigate the characteristics affecting the adoption of multiple learning innovations rather than the adoption of just a single innovation, as suggested by Tornatzky and Klein (1982). One key reason for this is because the investigation of a single innovation makes the distinction between the features of a single innovation and the actual predictive ability of the attributes across different innovations harder. For instance, it was found that studying a single innovation/technology might have a significant moderating effect (Schepers & Wetzels, 2007). Additionally, studying a single innovation does not allow for a robust generalisation to a wider population of innovations (Tornatzky & Klein, 1982).

This study does not look at the adoption of a specific technology or innovation, but rather, at a more generic adoption of different innovations that can enhance learning. In so doing, this investigation will help in testing and validating the characteristics incorporated by the model across different innovations, allowing for a wealth of information and appropriate validation of the model. Pooling such data across different innovations/technologies or organisations is consistent with previous research in the technology adoption field (Compeau & Higgins 1995; Venkatesh & Davis 1996; Nistor et al. 2010).

Based on the above, measures adopted from the various theories and models will be modified as needed to reflect this. Survey questions need not include a specific name of a system, technology or innovation, but rather a general wording that conveys the meaning clearly.

The following is a discussion of the different constructs incorporated within the model, the hypotheses that will be tested, and the various moderating variables that will be examined.

3.1 Model Constructs and Hypotheses

The work presented in this study builds on the UTAUT (Venkatesh et al., 2003) as a base model. Additionally, Moore and Benbasat's (1991) work, which is based on Roger's (2003) earlier work, will also be considered. Moreover, the theoretical model proposed by this study modifies and extends on those theories to explain the adoption of different innovations that may enhance learning.

The theoretical research model postulates ten constructs (Figure 3.1) that determine the behavioural intention to adopt and use innovations. Additionally, the actual use of an innovation is also included and will be investigated. The following figure illustrates the theoretical model to be tested by this study. Discussion of each of these constructs follows throughout this chapter.

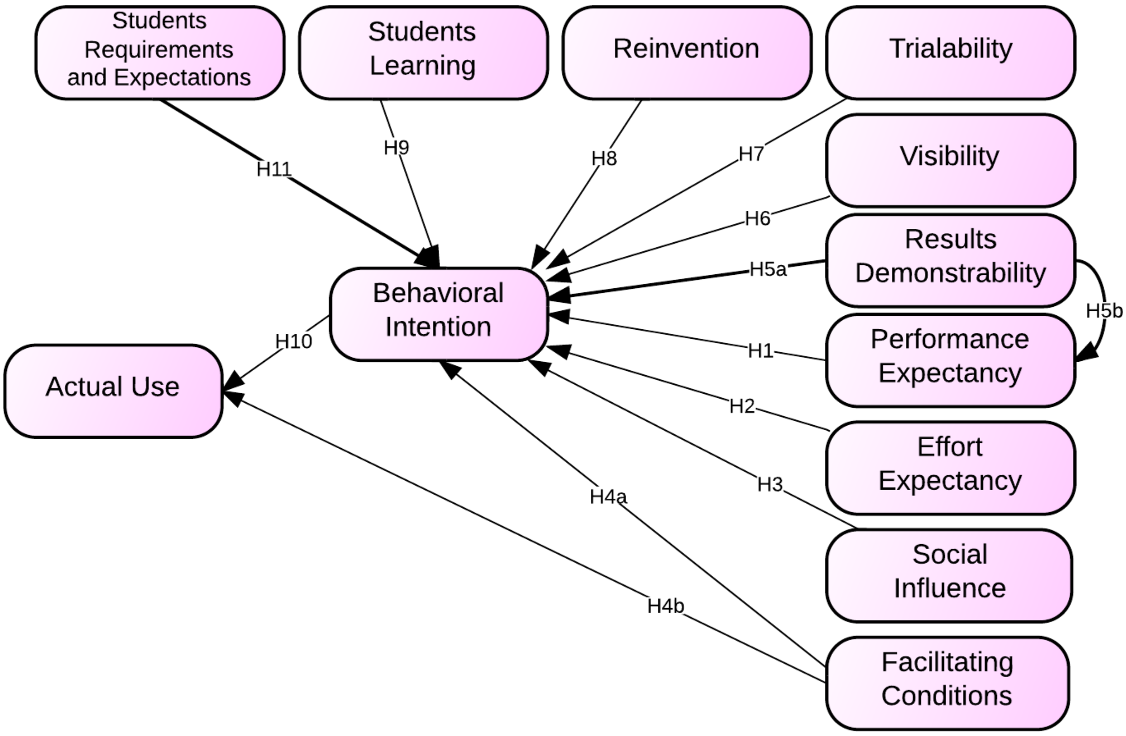

Figure 3.1 Theoretical Model for Innovation Adoption in UK Universities

This research also examines seven moderating variables (gender, age, work experience, education, voluntariness, teaching hours, and country) that may have a varying influence on some or all of the relationships postulated in the model.

3.1.1 UTAUT Constructs

We start by discussing constructs that were derived from the UTAUT model.

3.1.1.1 Performance Expectancy

Performance expectancy is defined as the degree to which an individual believes that using the system (or innovation) will help him or her achieve a better job performance (Venkatesh et al., 2003). This is very similar to the relative advantage innovation attribute (Rogers, 2003; Greenhalgh et al., 2005). There are five constructs used by different models that are related to the performance expectancy construct proposed by the UTAUT. These are: perceived usefulness, relative advantage, extrinsic motivation, job-fit, and outcome expectations

Carter and Belanger (2005) in their study decided to initially look at the relative advantage and the usefulness constructs separately. However, they noted later that conceptually, both of these constructs were very similar, referring to how an innovation may help in achieving some goal. Hence, they decided to drop the perceived usefulness construct from further analysis, as both mentioned constructs essentially captured the same concept.

Performance expectancy is considered the strongest or one of the strongest predictors of intention (Davis, 1989; Kijsanayotin, Pannarunothai, & Speedie, 2009; Lakhal et al., 2013; Sumak et al., 2010; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

An example of this construct within a university context is when a staff member perceives that using a technology like the e-mail would help him perform better, reduce workload, or contact students easily.

In the context of this study and consistent with previous studies, the author hypothesises that performance expectancy will have a positive influence on the behavioural intention to use the learning innovation:

$H1_0$: Performance expectancy will not have a significant positive influence on behavioural intention to use a learning innovation.

$H1_1$: Performance expectancy will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.1.2 Effort Expectancy

Effort expectancy is defined as the degree of unease associated with the use of the system (or innovation) (Venkatesh et al., 2003). The UTAUT integrated three constructs related to this concept. These constructs are: perceived ease of use, complexity, and ease of use.

As noted by Carter and Belanger (2005) the perceived ease of use construct from TAM is similar to the complexity construct from IDT. Also, according to Kijsanayotin et al. (2009), the effort expectancy concept within the UTAUT is similar to the perceived ease of use construct in TAM.

Although many studies have shown that perceived ease of use or effort expectancy had a significant influence on intention (Davis, 1989; Kijsanayotin et al., 2009; Moore & Benbasat, 1991; Oye, A.Iahad, & Ab.Rahim, 2012a; Thompson et al., 1991), others did not find such influence (Jong & Wang, 2009; Park, 2009; Selim, 2003; Sumak et al., 2010). Chau and Hu (2002) argued that, in their case, this might have been as a result of the competencies of the professionals who are more aware of the technologies or are able to work with them faster than others. Therefore, they give less weight to the ease of use of the innovation.

An example of this construct within a university context is when a staff member perceives that using a technology like Moodle (an e-learning system) is very easy.

In the context of this study, the author hypothesises that effort expectancy will have a positive influence on the behavioural intention to use the learning innovation. This would allow the researcher to test the influence; to find out if there is indeed such influence or not:

$H2_0$: Effort expectancy will not have a significant positive influence on behavioural intention to use a learning innovation.

$H2_1$: Effort expectancy will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.1.3 Social Influence (SI)

Research into innovation or technology adoption found that social or peer influences affect the adoption and diffusion of innovations (Jacobsen, 1998; Rogers, 2003; Venkatesh et al., 2003).

Social influence is defined in the literature as the degree to which use of a certain system (or innovation) is influenced by peers. For instance, if a teacher decided to use an iPad in his lectures, social influence would be what he thinks are the opinions others (i.e. peers) have of him while using the iPad in the classroom. Venkatesh et al. (2003) integrated a number of constructs that had already been established and tested by others into the social influence construct. These other constructs are: subjective norms, social factors, and image.

Although findings of studies carried out by many scholars suggest the importance of social influence in determining innovation or technology adoption (Sheppard et al., 1988; Ajzen, 1991; Venkatesh & Davis, 2000; Rogers, 2003; Venkatesh et al., 2003; Kijsanayotin et al., 2009; Sumak et al., 2010; Lakhal et al., 2013), Chau and Hu (2002) found that subjective norm had no significant effect on behavioural intention.

Venkatesh et al. (2003) in their study found that none of the social influence constructs studied were significant in a voluntary context, becoming only significant when the use of the technology or innovation is mandated.

An example of this construct within a university context is when a staff member perceives that all his peers are using discussion forums with their students, and therefore, he should do the same. This is a demonstration of the influence of this construct.

In the context of this study, the author hypothesises that social influence will have a positive influence on the behavioural intention to use the learning innovation. This would allow the researcher to investigate if, in this context, social influence would have any significant influence. This is hypothesised as:

$H3_0$: Social influence will not have a significant positive influence on behavioural intention to use a learning innovation.

$H3_1$: Social influence will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.1.4 Facilitating Conditions (FC)

Facilitating conditions are defined as the degree to which an individual perceives that the use of a certain system (or innovation) is supported via proper organisational and technical infrastructure. The facilitating conditions construct captures the concepts of three constructs used in previous models (Venkatesh et al., 2003): perceived behavioural control, facilitating conditions, and compatibility.

The existence of technical support helps staff members overcome complexities or difficulties they may face and could lead to increased staff satisfaction (Shea et al., 2005). Shea et al. (2005) referred to it as a crucial element in the success of online teaching. In their study, academic staff members were more likely to teach or continue teaching online if technical support was available. The use of online teaching approaches and technologies is considered a learning innovation. It is likely that technical support is crucial for the successful adoption of many learning innovations.

Findings of a number of studies in the information technology and adoption field demonstrated that the facilitating conditions construct have a positive influence and is a significant predictor of the intention to use (e.g. Jong & Wang 2009; Lakhal et al. 2013) or innovation (e.g. Technology) use (Moore & Benbasat, 1991; Thompson et al., 1991; Venkatesh et al., 2003). However, according to Venkatesh et al. (2003), facilitating conditions becomes insignificant in predicting intention when both performance expectancy and effort expectancy constructs are present in the same model. A study by Al-Shafi (2009) into e-government adoption also confirmed this.

An example of this construct within a university context is when a staff member wants to use certain software but is concerned with the availability of technical support within the unviersity in case any help was needed.

In the context of this study, the author hypothesises that facilitating conditions will have an influence on both behavioural intention and actual use. This would allow for re-testing of both relationships to see which of the previous findings above are true in the context of this study. This is hypothesised as:

$H4a_0$: Facilitating conditions will not have a significant influence on behavioural intention to use a learning innovation.

$H4a_1$: Facilitating conditions will have a significant influence on behavioural intention to use a learning innovation.

$H4b_0$: Facilitating conditions will not have a significant influence on actual use of a learning innovation.

$H4b_1$: Facilitating conditions will have a significant influence on actual use of a learning innovation.

3.1.1.5 Behavioural Intention (BI)

The intention to use or perform has been regarded as a strong predictor to the actual behaviour itself (Ajzen, 1991). Behavioural intention is the individual's readiness to perform a specific action or behaviour (Davis, 1989). In general, the stronger the intention is to perform a certain behaviour, the more likely such performance will take place(Ajzen, 1991). It is also argued that the higher the four previously discussed key constructs of

PE, EE, SI, and FC are, the higher the BI and Use will be (Venkatesh et al., 2003).

An example of this construct within a university context is when a staff member intents to use a certain teaching method.

In the context of this study, consistent with previous studies, it is expected that the intention to use a learning innovation will positively influence its use. This is hypothesised as:

$H10_0$: Behavioural intention to use a learning innovation will not have a significant positive influence on actual use of the learning innovation.

$H10_1$: Behavioural intention to use a learning innovation will have a significant positive influence on actual use of the learning innovation.

Note that the number given to this hypothesis is eleven because it will be the last one to be tested by the researcher.

3.1.1.6 Actual Use (U)

Actual use is the adoption and use of the technology or innovation. This is a dependent variable that had been used by many of the technology adoption theories and models, some of which were discussed earlier (e.g. TRA and TPB). Both TRA and TPB posited that individual's behaviour (i.e. use) is influenced by the preceding forming intention to perform it (Agarwal, 2000). Many have found that actual use correlated with behavioural intention or was significantly influenced by it (e.g. Davis et al., 1989; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010; Venkatesh et al., 2003).

In this study, the author will investigate the influence that may be caused by the independent constructs, discussed in this section, on this dependent construct.

3.1.2 IDT Constructs

In this section, we discuss other constructs that received some attention in the literature that are considered important to the adoption of innovations or technologies.

3.1.2.1 Results Demonstrability

Moore and Benbasat (1991) defined results demonstrability as the "tangibility of the results of using the innovation". Similarly, Karahanna et al. (1999) defined result demonstrability as "the degree to which the results of adopting/using the IT innovation are observable and communicable to others".

The more visible and demonstrable the advantages of an innovation to others, the more likely it will be adopted (Moore & Benbasat, 1991; Rogers, 2003). This was reinforced by Venkatesh and Davis (2000) who found that results demonstrability significantly influenced user acceptance.

Being exposed to the results of certain innovations will help reduce possible perceived risks of adoption (e.g. due to novelty and uncertainties) individuals may have as they become more aware and familiar with the innovation (Wejnert, 2002).

Similarly, Agarwal and Prasad (1997) in their study found a significant correlation between result demonstrability and behavioural intention. Karahanna et al. (1999) after discussing the results of Moore and Benbasat (1991) and Agarwal and Prasad (1997) decided to test the effect of results demonstrability on the adoption behaviour. They found that results demonstrability is significant for potential adopters.

An example of this construct within a university context is when a staff member notices how a colleague has benefited greatly from using certain software or tool. The focus here is on the outcomes.

Therefore, the study will explore the possible direct influence between results demonstrability and intention, hypothesised as:

$H5a_0$: Results demonstrability will not have a significant positive influence on behavioural intention to use a learning innovation.

$H5a_1$: Results demonstrability will have a significant positive influence on behavioural intention to use a learning innovation.

In the same vein, Venkatesh and Davis (2000) looked at results demonstrability as an antecedent for perceived usefulness. Their findings have shown that results demonstrability was significant as a determinant of perceived usefulness across four different studies and three time periods. Similar results were also reported by Jonas and Norman (2011).

Since the UTUAT incorporates perceived usefulness into the performance expectancy construct, this study will also explore, where appropriate in a later stage, if results demonstrability has any influence on the performance expectancy construct. Such influence should logically exist because if a potential adopter sees positive results as a result of innovations adopted by others, the potential adopter may perceive the innovation as being more beneficial. This is hypothesised as:

$H5b_0$: Results demonstrability will not have a significant positive influence on performance expectancy of using a learning innovation.

$H5b_1$: Results demonstrability will have a significant positive influence on performance expectancy of using a learning innovation.

3.1.2.2 Visibility

Closely related to the demonstrability of the results discussed above is the visibility of the innovation itself while being used. Rogers (2003) argued that some innovations are easy to observe or communicate to others while other innovations are not. He also stated that observability of an innovation is positively related to its rate of adoption. Being exposed to an innovation and its advantages may help reduce uncertainties or fears, leading to a more favourable decision with regard to the adoption of an innovation (Wejnert, 2002).

An example of this construct within a university context is when a staff member can easily see his colleague using an iPad to carry to achieve various tasks. The focus here is on being able to see the innovation itself rather than its outcomes as is the case in the previous construct.

This study will explore the possible direct influence between visibility and intention, hypothesised as:

$H6_0$: Visibility of the learning innovation will not have a significant positive influence on behavioural intention to use a learning innovation.

$H6_1$: Visibility of the learning innovation will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.2.3 Trialability

Trialability is defined as the possibility to experiment, on a limited basis, with an innovation. Some studies confirmed the significant importance of trialability to adoption (e.g. Suoranta, 2003; Odumeru, 2013).

Moore and Benbast (1991) argued that trialability should be of more importance to those adopting innovations at their own risk. However, in their study, they found it to be a weak predictor of adoption. As they explain, this may be as a result of the organisation's efforts to make the innovation or technology available for the individual adopter without any risks.

An example of this construct within a university context is when a staff member gains a first-hand experience of how a certain teaching method performs in the classroom.

In this context of this study, university academics are likely to be adopting and testing new innovations. These innovations may yet to be acknowledged by top management or social peers. Therefore, this will be tested and is hypothesised as:

$H7_0$: Trialability will not have a significant positive influence on behavioural intention to use a learning innovation.

$H7_1$: Trialability will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.2.4 Reinvention

Rogers (2003) based on his review of the literature stated that If the innovation can be adopted, changed, modified or improved to suit individuals' circumstances or needs, then, the innovation will be adopted more easily. Hence, for many adopters, reinvention occurs during the implementation stage of the innovation-decision process. On the contrary, the inability to change or alter the innovation prior to its adoption may lead to its rejection, especially if the innovation was not compatible with the individual's needs.

The Minnesota Innovation Research Program concluded their studies by saying: "Innovation receptiveness, learning, and adoption speed are… Inhibited when end-users [adopters] are provided with no opportunities to re-invent innovations that were initially developed elsewhere" (Rogers, 2003). Rogers (2003) also explored other studies that investigated the reinvention of a number of innovations and found that in many cases, reinvention occurred.

Similar to the previous constructs, perceptions can help in determining whether the flexibility of a certain innovation, more specifically, the possibility for the potential adopter to change the innovation to suit his or her needs, would influence the behavioural intention to adopt it.

An example of this construct within a university context is when a staff member decides that a certain teaching method should be changed or modified to yield better results.

The issue of reinvention was not investigated previously in technology or innovation adoption theories or models and it is worth investigating further. Hence, the proposed hypothesis is:

$H8_0$: Reinvention will not have a significant positive influence on behavioural intention to use a learning innovation.

$H8_1$: Reinvention will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.3 Education Constructs

In addition to the constructs discussed above, there are two important constructs that were not considered in existing innovation adoption theories and models. These are: Students' requirements and expectations and Students' learning.

Both of these proposed constructs are considered important within universities and similar educational institutions. However, whether they influence the adoption of innovations or not is worth investigating.

3.1.3.1 Students' Requirements & Expectations (SRE)

As discussed earlier in this thesis in the (section 1.1 above Issues Facing UK Universities), the increase in tuition fees came with an increasing demand for accountability and increased expectations as parents, students, and other stakeholders (e.g. sponsors) are expecting to get good value for money. This arguably leads to the need to give more attention to students in order to learn or have knowledge of their requirements or expectations, in order to meet or exceed them. Otherwise, students will be dissatisfied, and no university can be successful without its customers.

As noted by Asitn (1985), students can certainly transfer or leave programs that they do not find to be appropriate or meet their expectations. This could also influence more students to leave or not even apply, as those that did not enjoy or find a certain course or program useful are likely to let their friends or others know.

Being innovative and ahead of the competition requires being responsive and flexible to students' expectations and requirements, at least to a certain degree.

Although within a different context, a study into successful commercial innovations in two science-based sectors of industry found that successful innovators were those that had a greater understanding of the customers' needs (Science Policy Reseaech Unit, 1972). Despite the difference in the context, there is no reason to expect that such finding does not apply to the HE sector. A better understanding of students' requirements and expectations could actually help universities in providing better value while being competitive, likely leading to more students and additional funding.

Moreover, although usually confined, there are various innovative methods and approaches being used within universities. To ensure that such innovations help add more value, there is a need to understand how they help meet or exceed students' requirements and expectations. Staff may choose to adopt and use some of these innovations to improve teaching, comply with their students' needs, stay up to date, or gain better reputation as excellent and innovative teachers (Peluchette & Rust, 2005; Roberts, Kelley, & Medlin, 2007; Spodark, 2003).

An example of this construct within a university context is when a staff member perceives that the use of an e-learning video conferencing tool can help meet or exceed students' requirements and expectations.

Based on the above, the author hypothesises that:

$H11_0$: Students' requirements & expectations will not have a significant positive influence on behavioural intention to use a learning innovation.

$H11_1$: Students' requirements & expectations will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.3.2 Students Learning (SL)

One important outcome of higher education institutions should be that the students emerge as better learners (Brown et al., 1997), allowing them to cope with the outside world and work requirements while also continuing to learn. Staff can adopt and use various innovations (e.g. instructional technologies or teaching methods) to enhance students learning (Kulik & Kulik, 1987; Peluchette & Rust, 2005; Roberts et al., 2007; Spodark, 2003). There is a strong call for EU universities to strive to improve the quality of teaching and learning (Modernization of Higher Education Group, 2013).

Sugar et al. (2004) examined the primary reasons for teachers' adoption of instructional technology. These reasons included: career preparation for students, exposure to new technologies and skills, engaging and sparking students' interest. Similarly, enhancing students' learning was found to be a significant factor influencing the adoption of certain innovations in the classroom (Roberts et al., 2007).

An example of this construct within a university context is when a staff member perceives that the use of an e-learning video conferencing tool can help improve students' learning.

Based on the above, the author hypothesises that:

$H9_0$: Students' learning will not have a significant positive influence on behavioural intention to use a learning innovation.

$H9_1$: Students' learning will have a significant positive influence on behavioural intention to use a learning innovation.

3.1.4 Moderators

Taking into account possible moderator variables when studying innovation or technology adoption may help explain some of the inconsistencies between the constructs or the differences in the explaining power found between the various technology adoption models in the literature (Sun & Zhang, 2006) and even between various studies using the same models but in different contexts (e.g. different countries or organisations). Similarly, Venkatech et al. (2003) argue that the use of moderators would possibly enhance the predictive validity of the various adoption models. Therefore, this study investigated the moderating effect of a number of factors: gender, age, work experience, level of education, voluntariness, teaching hours, and the country.

Gender is the first moderator to be considered in this study. Sun and Zhang (2006) suggested that gender differences could influence technology adoption. Venkatesh and Morris (2000), based on measuring at three different points in their study, concluded that men's usage decisions were strongly influenced by the usefulness perception, while women's were strongly influenced by ease of use and subjective norm perceptions. Therefore, the difference between men and women is expected to be significant. Venkatesh et al.'s (2003) findings also suggest that gender moderates the effects of PU, PEOU, and SN constructs on BI. This was also supported by Sun and Zhang's (2006) findings. Peluchette and Rust (2005) also reported that male and female faculty had significant differences with regard to instructional technology preference.

Age will also be considered as a moderator that may have an influence on the adoption of learning innovations. Venkatesh et al. (2003) found that younger users gave more weight to extrinsic reward (equivalent to PU). Moreover, as a result of the negative effect caused by increased age on attention and stimuli (Venkatesh et al., 2003), it is implied that PEOU would be a stronger determinant for BI for older users. Sun and Zhang (2006) found that age moderated a number of relationships. On the contrary, Quazi and Talukder (2011) did not find a significant influence of age over the perception or usage of technological innovations.

Work experience will also be looked at as a possible moderator. While some studies (e.g. Davis 1989; Venkatesh 2000) looked the experience of working with the technology as a possible moderator, in this study, this construct was not captured and work experience was captured instead.

The **level of education** is another moderator that will be considered in this study. Quazi and Talukder (2011) found that training and educational qualifications influence the perception of technological innovations. Others have also looked at the influence of the level of education (Agarwal & Prasad, 1999; Wu & Lederer, 2009).

Voluntariness will also be considered as a possible moderator. This refers to whether or not the adoption is mandatory and how that may influence the adoption decision in some way (Moore & Benbasat, 1991). Venkatesh and Davis (2000) tested the role of voluntariness and its influence over the relationship between SN -> BI. This confirmed that SN had a significant direct effect on BI in the mandatory usage context. Based on the comparison done by Venkatesh et al. (2003), certain relationships (e.g. effects of social influence) in the model are expected to be significant when the use of an innovation is mandated. They then tested the moderation effect of voluntariness and confirmed these findings. This was also supported by Sun and Zhang's (2006) findings. In short, previous research collectively confirmed the importance of voluntariness in influencing use intentions (Wu & Lederer, 2009).

The author did not find any studies that investigated teaching hours, as well as different countries, and how they may possibly act as moderating variables. Nonetheless, they are included in this study to test whether there are any influences caused by them.

3.1.5 Mediations

In certain situations, the relationship between the IV (independent variable) and the DV (dependent variable) may be complex in that there might be some influence caused by a third unexplored variable that may be mediating the effect explaining some of the variance in the DV. Hence, to ensure that there are no more accurate explanations for the direct IV to DV relationships between the various constructs in the model, mediation testing will be carried out by the researcher, where applicable (because for mediation testing there needs to be more than one dependent variable).

3.2 Summary

In this chapter, the goal was to develop the learning innovation adoption model that could help explain the adoption of learning innovations within UK universities. Based on a number of existing theories and models, ten constructs were derived from the literature. Additionally, two education-related constructs were also proposed. Moderating variables were also defined, but also, where applicable, mediating effects will be investigated.

Eleven hypotheses were postulated in this chapter. Many of these hypotheses are for relationships that have been tested previously but need to be re-examined as a result of introducing a modified integrated model, modifications made to the measures, and because the new model is tested for the first time in this context.

The following table summarises the hypotheses that will be tested:

#	Hypothesis	Literature Support
$H1_1$	Performance expectancy will have a significant and positive influence on behavioural intention	Davis, 1989, Venkatesh and Davis, 2000; Greenhalgh, 2005; Rogers, 2003; Venkatesh et al., 2003; Kijsanayotin et al., 2009; Sumak et al., 2010; Lakhal et al., 2013
$H2_1$	Effort expectancy will have a significant and positive influence on behavioural intention	Davis, 1989; Moore and Benbasat, 1991; Thompson et al., 1991;Kijsanayotin et al., 2009; Oye et al., 2012b
$H3_1$	Social influence will have a significant and positive influence on behavioural intention	Jacobsen, 1998; Sheppard et al., 1988; Ajzen, 1991; Venkatesh and Davis, 2000; Rogers, 2003; Venkatesh et al., 2003; Kijsanayotin et al., 2009; Sumak et al., 2010; Lakhal et al., 2013
$H4a_1$	Facilitating conditions will have a significant influence on behavioural intention	Jong and Wang, 2009; Lakhal et al., 2013

$H4b_1$	Facilitating conditions will have a significant influence on actual use	Moore and Benbasat, 1991; Thompson et al., 1991; Venkatesh et al., 2003
$H5a_1$	Results demonstrability will have a significant positive influence on behavioural intention	Moore and Benbasat, 1991; Agarwal and Prasad, 1997
$H5b_1$	Results demonstrability will have a significant positive influence on performance expectancy	Venkatesh and Davis, 2000; Jonas and Norman, 2011
$H6_1$	Visibility will have a significant and positive influence on behavioural intention	Rogers, 2003; Wejnert, 2002
$H7_1$	Trialability will have a significant positive influence on behavioural intention	Rogers, 2003; Suoranta, 2003; Odumeru, 2013
$H8_1$	Reinvention will have a significant and positive influence on behavioural intention	Rogers, 2003
$H11_1$	Students' requirements and expectations will have a significant and positive influence on behavioural intention	None. Proposed by the researcher
$H9_1$	Students' learning will have a significant and positive influence on behavioural intention	None. Proposed by the researcher

$H10_1$	Behavioural intention will have a significant positive influence on actual use	Ajzen, 1991; Venkatesh et al., 2003

Table 3.1 Summary of Hypotheses with Literature Support

Hypotheses testing will be done in a later stage, during the examination of the structural model and the significance (p-value) of path estimates, as they represent the various relationships in the model, some of which were hypothesised above.

4 Research Design

In the previous chapter, the learning innovations adoption model was developed based on established theories and models in the innovation/technology acceptance literature. The possible relationships between the different components were highlighted. Additionally, hypotheses were developed in order to test whether or not these relationships exist.

In order to test the conceptual model previously presented, there is a need to collect empirical evidence that will then be statistically analysed for hypotheses testing. However, in order to successfully collect relevant accurate data, there is a need to first define a research design that is most appropriate for this study. This is the main objective of this chapter.

Creswell (2009) defined the research design as “the plan or proposal to conduct research” which takes into account three components, the “intersection of philosophy, strategies of inquiry, and specific methods”.

There are three types of designs: qualitative, quantitative, and mixed methods. Qualitative and quantitative designs may appear to be opposite or contrary methodologies, when in fact, they should actually be looked at as though they were “different ends of a continuum” (Creswell, 2009). A study could be more qualitative in nature than it is quantitative, or the opposite can be true. Mixed methods approaches reside in between, as mixed methods approaches incorporate elements of both qualitative and quantitative methodologies (Creswell, 2009).

There are three main components that help to shape or define the type of the research design that is utilized (Cohen, Manion, & Morrison, 2011). The following figure illustrates these components:

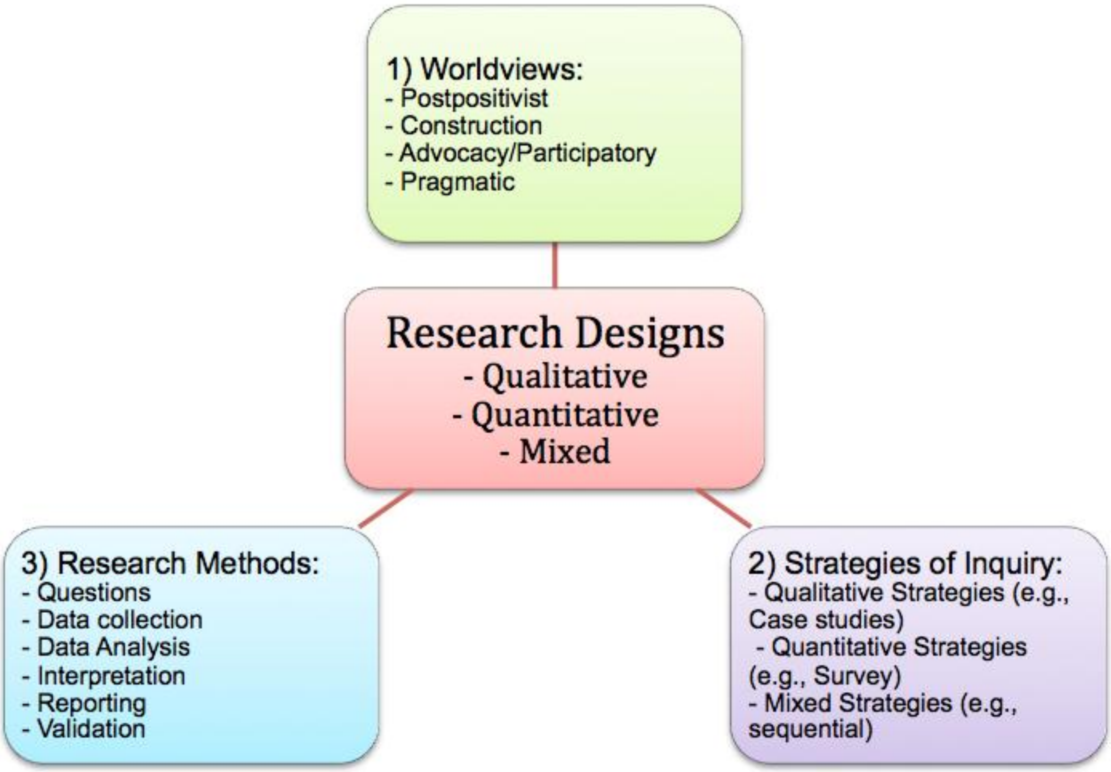

Figure 4.1 Components of Research Design

Creswell (2009) argues that researchers need to think about the research paradigm or worldview assumptions that they convey in the study. In addition, the approaches or strategies used to answer questions related to the worldview and the specific research ways or methods used should be considered, as all of these components contribute to a research design being quantitative, qualitative, or mixed methods.

4.1 Research Paradigm

Research into information systems (IS), where the UATAUT and similar models were built and validated, is not necessarily constrained to a single theoretical perspective (Orlikowski & Baroudi, 1991). However, the positivism paradigm or approach is considered a primary epistemology in the IS field (Straub, Boudreau, & Gefen, 2004).

The positivist paradigm calls for the development and testing of sound theoretical frameworks or theories (Hoe, 2008). This is similar to what this study aims to achieve. Therefore, consistent with similar previous research (Al-Shafi, 2009; e.g. Davis, 1989; Venkatesh et al., 2003; Venkatesh & Morris, 2000), this study adopts a positivist approach.

4.2 Research Approach/Strategy of Inquiry

The decision on what research approaches and analytical methods are appropriate for the study relies on the research problem and the goals of the study (Biggam, 2008; Walliman, 2006). While selecting the research approach, researchers should also consider both the type of inquiry being made and the type of information that is needed to answer the question (Bell, 2010).

In this research, the purpose is to validate an extended model for the adoption of learning innovations within universities in UK. This study's theoretical model is based on similar models and theories that exist in the innovation/technology adoption literature. Examples include the TAM (Davis et al., 1989; Davis, 1985), the UTAUT (El-Gayar & Moran, 2006; Oshlyansky et al., 2007; Venkatesh et al., 2003), and the innovation diffusion theory (Moore & Benbasat, 1991; Rogers, 2003). However, in addition to the constructs proposed and tested by these models or theories, this study proposes additional constructs that are unique to the higher education context.

Based on the needs of this study and in line with similar studies reported above and in the literature, the research design adopted is a **quantitative** research approach.

A survey quantitative research approach is more appropriate than is a qualitative approach as it allows for access to a breadth of information that can help in testing the theories and in examining relationships between different variables or components (Creswell, 2009), as well as allows the researcher to generalise, the findings to the population of the study if an appropriate response was obtained. Such approach is consistent with studies in the innovation and technology adoption field.

4.3 Data Analysis Approach

Hair, Black, Babin, and Anderson (2010) recommends that researchers should define approaches to data analysis early, to ensure that instruments used are able to collect the appropriate data. This is certainly important as otherwise, data collected may not be appropriate for the selected data analysis approach.

In this study, data will be analysed in order to confirm or reject the hypotheses representing different relationships in the model. Therefore, Structural Equation Modelling (SEM) will be used to analyse the data. Many studies in the field have used SEM or multiple regression and path analysis, both of which are incorporated into SEM, in order to validate different models (Carter & Bélanger, 2004; Davis et al., 1989; Davis, 1985; Venkatesh et al., 2003; Venkatesh, 2000). SEM is considered a superior approach to multiple regressions and path analysis as in addition to hypotheses testing, it can help researchers uncover and test other relationships that may be suggested by the software package, based on the analysis of the captured data. SEM also allows for easy testing of effects such as: moderation, mediation, and interaction. Most SEM software also provides the possibility to use bootstrapping, a re-sampling technique that helps in investigating effects further as well as helps researchers overcome some issues that may result from violations in multivariate assumptions.

The SEM approach accepts ordinal or interval data, although advancements in analysis software now allow for the use of other types of data with this analytical approach. However, the use of other types of data has yet to catch up in the adoption field especially when using SEM. Established measures in the adoption literature are using Likert scale questions to capture information. The use of other type of questions would require robust development, testing and validation and may prove to be unreliable or appropriate. The researcher leaves such development and testing to other studies wishing to push our understanding of adoption in that direction. Therefore, because the aim in this study is to validate an extended and modified model rather than develop new measures, the use of Likert scale questions to capture information related to the various measures is deemed appropriate.

4.4 Use of Online/Web-based Survey

This study made use of an online questionnaire as a data collection instrument. The use of an online questionnaire helps realise a number of benefits (Cohen et al., 2011; Gillham, 2007; Sarantakos, 2005) such as:

- A link to the online questionnaire can be easily sent to a large group of people quickly.
- Allows for generalizability of findings when done properly.
- Using an online questionnaire saves costs and time associated with printing and posting (or delivery in person).
- As a result of the online questionnaire being open, data can be collected 24 hours every day. Respondents who are busy at work have the choice to participate when they are free.
- Depending on the tool used to design and deliver the survey, it is possible to build logical processes where certain questions are hidden/shown based on the respondent's answers. This way, irrelevant questions are removed and more relevant information is presented based on the respondent's circumstances. This helps ensure that data collected are more accurate.
- Responses can be automatically captured and saved to database, reducing time needed to manually input data for each individual respondent.
- Data collected are usually stored in a data file that is ready for analysis with SPSS or similar software packages. This reduces time needed to collect, sort, and prepare the data.
- Some online questionnaire creation tools offer a much easier way to handle participants' information as well as the sending and tracking of invitations and reminders.

4.4.1 Ethical Considerations

In line with ethical and other practical considerations some of which are required standards within the University of Warwick, a number of measures were put in place. First, informed consent was obtained by adding an information page at the start of the online questionnaire explaining the various ethics–related aspects of the study, as well as informing them that starting the survey is considered to be consent for participation. A link to a more detailed version of the ethics–related aspects of the study was also provided in the first page. Also, full contact details for the researcher were present in the invitation letter, the first page of the survey, and in the detailed ethics file.

Second, participation in the study is voluntary because participants have decided willingly to click on the link leading to the online questionnaire, and then, they voluntarily pressed on the button to start the survey. Additionally, they have full control and they are able to withdraw from participating at any time prior to submitting the last page. Responses for those who withdrew were removed.

Third, anonymous participation was important and was guaranteed to participants. In general, although the e–mail addresses and full names of those who were invited to participate were available to the researcher, those were only used in the invitation letter to deliver a more personalised experience where the respondent is greeted by his or her full name. However, once the respondents participated, their responses were completely anonymous.

Fourth, to encourage participation, both the first page of the survey and the ethical-information file provided included information of the incentives offered by the study (see below). Links to the various incentives were presented at the end of the study. If, for any reason, the links provided were not saved by respondents, they were able to contact the researcher to have the links resent.

Finally, at the end of the survey, the respondents had the choice to enter their e-mail addresses in case they wanted to receive a summary report at the end of the study. E-mail addresses are kept separately and will be used later on to send the summary report and a special thank you letter for their participation.

Next, the author discusses how the instrument and the measures used by this study were developed.

4.5 Instrument Development and Measures

The instrument used in this research was based on measures developed and validated by UTAUT. However, modifications had to be made to the measures to ensure that they were suitable for use in an educational context and reflect the need to measure for different innovations that enhance learning. Additionally, the researcher constructed measurement scales for constructs that did not have apparent measures in the technology or innovation adoption literature. For instance, the researcher proposed several measures for the students' requirements and expectations, as well as the students' learning constructs.

The researcher assessed all measures for face validity first by getting prior feedback from five academic staff members at Warwick Manufacturing Group at The University of Warwick.

The reliability of the measures was then tested using a pilot study where the questionnaire was distributed to all staff members within The University of Warwick. Out of 37 staff members who started the questionnaire, only 23 completed it. Feedback for improving the questionnaire was also received from a number of respondents. Through their feedback, the instrument was improved. Section 4.7.2 (Pilot Study) below discusses at the pilot-testing phase.

The final instrument consisted of a number of parts. **Part 1** welcomes the participant and provides general information about the study, how to participate, and ethics-related information. Appendix 276 lists all the questions in the questionnaire.

Part 2, was designed to capture demographics-related information from respondents and provide any needed definitions to help respondents answer the questionnaire. Demographics-related information could then be used for multi-group moderation testing if appropriate. In order to be able to distinguish between adopters and non-adopters, a Yes/No question asked if the respondent had adopted any learning innovation before. Other questions were also used to inquire about the innovation in question, such as whether the adoption of the innovation was voluntary or mandatory.

Part 3 of the questionnaire included questions adopted from previous studies, which were modified to fit the context and purpose of this study. These questions were used to capture information related to the different constructs that may lead to the adoption of learning innovations. All constructs, aside from actual use, were measured on a 7-point Likert-type scales, ranging from 1= strongly disagree to 7 = strongly agree. Actual use was operationalized through a self-reported Yes/No measure in which the respondent is asked if he had previously adopted a learning innovation.

Moreover, with regard to measures adopted and used in Part 3, the researcher collected answers to these questions from adopters and non-adopters separately. This was automatically done based on questionnaire logic, which constructs this section of the questionnaire based on whether the respondent reported whether or not he or she has used a learning innovation before. The main reason for doing so is to present helpful information to adopters and non-adopters in order to help them understand the context of the questions asked. For example, when asking someone who has adopted a learning innovation before, we are interested in what his or her perceptions were prior to the adoption. On the other hand, for those that did not adopt a learning innovation before, we seek to understand their perceptions about a learning innovation that they are thinking of adopting.

The reliability and construct validity of the final measures are discussed in a later part of this study. Section 5.6.2 (Reliability and Validity) discusses the results of these tests and subsequent changes made (e.g. dropping of problematic items).

Despite the researcher's intention to use a short questionnaire, based on the measures adopted for the many constructs this study investigates, the resulting questionnaire was considered long. Therefore, there was a need for simple and useful incentives that encourage participation. Next, the author discusses the various measures taken to encourage participation in this study.

4.6 Encouraging Participation/Incentives

Staff members within the UK universities are busy and usually do not have enough spare time for outside research participation. This was clear to the researcher after investigating the issues facing UK universities earlier in this study. This was also confirmed by the very low participation received during the pilot-study phase as very few staff members participated. Therefore, to encourage participation, the researcher made use of a number of techniques and tools in an attempt to create more interest in the study.

Invitation e-mail design

To ensure that staff members actually take the time to open and read through the first e-mail asking for their participation, the researcher designed a nice looking e-mail that is compatible with all modern e-mail clients. Moreover, keeping in mind good practices for e-mail design typically adopted and used by businesses, the researcher made use of pictures, including adding a personal picture, to make the e-mail feel personal and stand out from the hundreds of e-mails staff members receive.

Each individual recipient of the e-mail invitation was greeted personally with his/her full name. This was also the case when they opened the questionnaire to participate. Such information was collected with their e-mails from their university's website. Such personalisation, the researcher hoped, could help encourage participation. Finally, the e-mail invitation also included a "benefits" section explaining what types of resources they would have access to once they completed the questionnaire.

The invitation e-mail can be seen in Appendix 2. The e-mail design was piloted with a number of staff members who found it interesting and who suggested some improvements.

Teaser/Sample Resources

To give potential participants a better idea of what to expect if they participated in the study and completed the online questionnaire, the researcher created a teaser/sample page sharing a number of useful links, as well as showing screenshots of an interactive website the researcher built specifically to encourage participation (see below). The link to this teaser page was included in the “benefits” section in the e-mail invitation.

Video explaining the need for the study

In addition to explaining the study and the need for it in words, the author created a short animation video. A link to the video was included in the e-mail invitation as well as at the beginning of the online questionnaire. The video was published on YouTube and can be accessed at any time through the following short URL:

http://youtu.be/FRVbgY5PM7U

After publishing and sharing the video, the author received good feedback through e-mails. Other researchers expressed their interest in creating similar videos to explain their studies or to share information with their students.

Access to useful resources for participants

To encourage participation in the study, the author created an interactive website highlighting many tools and technologies that can be used by educators, including mind mapping, survey video creations and other types of tools. Again, the researcher received good feedback from a number of participants in the study, in addition to many comments on the website itself. The website received thousands of visits. This online resource can be accessed through the following short URL:

http://TheEDHub.com

Since this is the main incentive to encourage participation, the URL was only shared with participants after they complete and submit the survey. Once these various incentives were prepared, the author started preparing for the main data collecting stage discussed next.

4.7 Data collection

This section briefly discusses the pilot and main study used, as well as how the samples were drawn. Response rate, demographics, data screening, and the analysis and statistical procedures followed in subsequent chapters are presented in the next chapter.

4.7.1 Pre-Test

The author did a pre-test of the questionnaire with four members of staff within the University of Warwick. The goal was to assess the content, wording, and explanation of the measures or questions and the overall questionnaire design. Feedback was then used to improve the research instrument.

4.7.2 Pilot Study

Following the good practices in research as pointed out in the research design literature (e.g. Bryman, 2008; Cohen et al., 2011), the survey questionnaire adopted by this study was pilot tested within the University of Warwick. Heads of departments within the university, in addition to some academic staff added manually, were contacted and asked to contribute and circulate the invitation to other academic staff members. One reminder was sent to departments that did not participate (i.e. no single response from the department was collected).

Out of 41 academics contacted, including all heads of departments, 37 responses were received. Some of these responses were partial responses and they were dropped.

Using 25 useable completed responses, the research instrument was tested for its reliability using Cronbach's alpha test. Results are presented in Appendix 22.

We note that the questions were worded in a way to be answerable by adopters and non-adopters using words like would/should. However, after the pilot study, to reduce possible confusion, the same questions were presented to both adopters and non-adopters while presenting a slightly different version for each.

After investigating of the results of the Chronbach's alpha test (Appendix 22), it was clear that one of the items in the scale related to the observability construct could be deleted to improve the score. The item was:

- **The results of using learning innovations are clear to me**

After careful consideration of Moore and Benbasat's (1991) work, the researcher found that the question that should have been deleted to improve the Chronbach's alpha score actually falls under the "results demonstrability" construct in their study. Therefore, it made more sense to split the observability construct into the two constructs suggested by the aforementioned authors in their study: results demonstrability and visibility. Doing so would possibly not only improve the reliability score, but would also allow for the capturing of information that is possibly related to the two different constructs. Therefore, the model was updated. This was also reflected in the previous chapter as both of these constructs were added (section 3.1.2 aboveIDT Constructs above).

Furthermore, items that were candidate for removal due to low reliability were also removed. The final questions used are presented in the full questionnaire in Appendix 2.

4.7.3 Main Study Sample Calculation

Once the data collection instrument was developed and tested in the previous pilot testing phase, it is now time to give attention to what sample should be used in the main study. This section discusses how the sample for the main study is calculated to ensure appropriate representation of the population of the study (UK universities).

4.7.3.1 Identifying the Base Sample Size

Because the aim is to statistically validate the hypotheses proposed by this study, there is a need for a large number of respondents (200+). Hence, a survey approach is deemed appropriate for this study. This goes in line with previous research in the same innovation/technology acceptance field (Carter & Bélanger, 2004; Davis et al., 1989; Davis, 1985; Venkatesh et al., 2003; Venkatesh, 2000).

Statistical approaches aiming to validate models such as Structural Equation Modeling (SEM) has a minimum requirement with regard to the number of observations that should be obtained. While opinions differ, some argue that more than 200 responses are deemed reasonable (Byrne, 2010; Hair et al., 2010; Hoe, 2008; Kline, 2012). However, there are recommendations to increase the sample size targeted in cases where there are many variables in the model. In this study, because there are 10 observed variables, the study considers 600 observations (i.e. responses) an appropriate base sample to target.

4.7.3.2 Response Rate Considerations

Results from the pilot study carried by the researcher indicate that the response rate would be low if heads of departments were contacted; most direct responses were from individuals who were contacted directly. The researcher believes that contacting individuals directly is a much safer option, as this would reduce the risk associated with a single staff member having the key decision of whether to pass it to others or not, in addition to other risks (e.g. not receiving the e-mail or not opening it). Moreover, the issues facing UK universities and impacting staff members discussed earlier in this study give indications that the response rate is likely to be very low. Therefore, a safe number of respondents to target would be 3000 responses (600/20%); 600 is the base sample size representing the required number of responses defined above and 20% being a safe margin.

Using a probability sampling approach is deemed to be an appropriate approach that is less biased, so as to be more likely to be representative of the whole population (Cohen et al., 2011).

A clustered sampling approach will be used to draw a representative sample of responses from across the different regions of the UK, allowing for an analysis of data to be carried out across the UK, but also within individual countries. Therefore, the researcher aims to collect a minimum safe response target of 3000 responses from each country; to allow the researcher to not only carry out a UK-wide analysis, but also, to be able to analyse the data by countries.

4.7.3.3 Sample Calculation for Individual Countries

When calculating sample sizes for individual countries based on the reported number of academic staff members, reported by the Higher Education Statistics Agency for the 2011-12 period (Higher Education Statistics Agency, 2011), the following is the probability sample calculated at confidence level 95% with the confidence interval being 2 (5% Margin of Error) for each country:

Country	Number of Academic Staff	Sample Size	Sample + Safe Margin (Sample Size/20% Response rate)
England	158395	2365	11825
Scotland	18580	2126	10630
Wales	6065	1720	~~8600~~ 6065*
Northern Ireland	4830	1604	~~8020~~ 3095*

*** Total number of academic members of staff is less than that required.**

Table 4.1 Sample Calculation for Individual Countries

The above calculation of the minimum representative sample, along with the safe margin, to target additional staff members due to the expected low response rate to be safe, is deemed appropriate for achieving a representative sample for individual regions (i.e. separate from the rest).

4.7.3.4 Sample for all The UK

In addition to taking the individual countries into consideration when calculating the sample size, there is also a need to consider the overall representation of these different countries to ensure that enough responses are collected in order to obtain the correct proportions across different regions. This is so that a higher level of analysis can also be applied (UK level). To ensure this, there is a need to calculate the number of responses required for each region to be appropriate. Hence, the following is a calculation of the required number of responses. This calculation is derived by taking the number of universities and academic staff members in each country into consideration (Higher Education Statistics Agency, 2011).

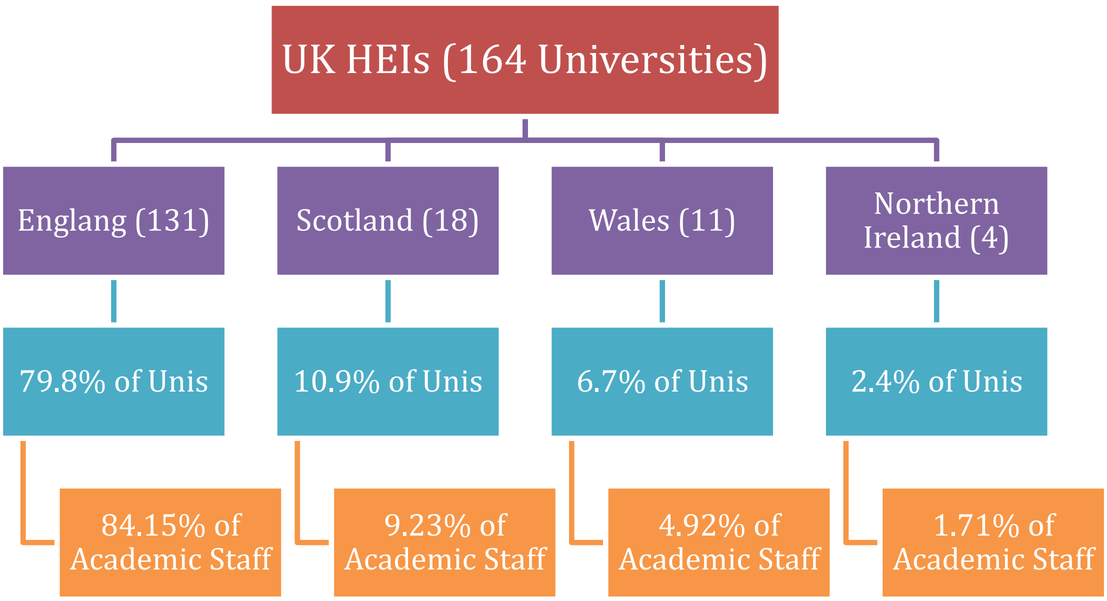

Figure 4.2 Sample Calculation for the UK

Based on the proportions calculated above for each region according to the unit of analysis, staff members, a representative sample of 2,370 academic member of staff should be appropriate to represent the whole population of

UK academic staff members. However, taking into account response rate considerations and to be safe, 11,850 academic staff members across the UK will be contacted. Therefore, responses would be split proportionally to:

Country	Number of Responses
England	9972
Scotland	1094
Wales	583
Northern Ireland	203

Table 4.2 Sample Calculation for the UK

4.7.3.5 Final Sample (Based on the above two calculation approaches)

Now that the researcher have identified the minimum required number of responses for statistical analysis, the number of required responses needed within each country to be representative to the country, and the number of responses needed for the overall sample to also be representative of the UK as a whole, below, the researcher discusses which universities will be contacted.

In order to get a better understanding of how many universities will be contacted, the researcher starts by calculating the average number of staff members for universities within each country. Based on official statistics reported above, the averages (academic staff divided by number of universities within the country) are

Country	Number of Academic Staff	Academic Staff Average
England	158395	1165
Scotland	18580	930
Wales	6065	811

Ireland	4830	774

Table 4.3 Academic Staff by Country

Since there are big differences in the average, the researcher believes that using the average for each region would be more accurate than using an overall average when calculating the number of institutions needed to fulfil the response rate needed from each region.

The number of universities to contact below is a rough estimated that is based on the larger of the two approaches calculated above (by individual countries and UK as a whole), to ensure sufficient data to be used for both. These numbers are found in the table below (Table 4.5).

Country	Target Number of Responses	Average number of academic members of staff per Institution within region	Expected number of Universities needed to be contacted (with the safe margin)
England	11825	1165	11
Scotland	10630	930	12
Wales	6065	811	8
Northern Ireland	3095	774	4

Table 4.4 Number of Universities to Contact by Country

The number of universities that will be contacted based on the table above **may increase or decrease** based on how many universities were needed to fulfil the target number of responses, since the sample will be pulled randomly of available universities. This is the case because some universities have either many more or far fewer academic staff members than the average. Therefore, when randomly selecting the universities to be contacted within each country, the total number of academic staff members will be summed for each university and added to the sample until the goal (units of analysis per country) defined in the above table (Table 4.5) is reached.

The **final sample** resulting from this somewhat complex procedure to draw the representative sample was the following universities:

1. Bangor University
2. The University of Birmingham
3. Cardiff Metropolitan University
4. Cardiff University
5. Glasgow Caledonian University
6. Heriot-Watt University
7. Queen Margaret University, Edinburgh
8. Royal Conservatoire of Scotland
9. St. Mary's University College
10. Swansea University
11. The Queen's University of Belfast
12. The Robert Gordon University
13. The University of Dundee
14. The University of East Anglia
15. The University of Edinburgh
16. The University of Glasgow
17. The University of Newcastle-upon-Tyne / Newcastle University
18. The University of Northampton
19. The University of Reading
20. The University of Stirling
21. The University of the West of Scotland
22. University College Falmouth
23. University of Abertay Dundee
24. University of Bedfordshire
25. University of Glamorgan
26. University of Ulster
27. University of Wales Trinity Saint David

4.8 Summary

In this chapter, the goal was to develop a research design that is appropriate and effective for the needs of this study; to collect empirical data that helps in validating the proposed theoretical model developed in the previous chapter.

Consistent with previous innovation or technology adoption studies, this study adopted a quantitative survey approach utilising a questionnaire data collection instrument.

Once the research design was ready, the author developed a research protocol for this study and submitted it to the BSREC ethics-overseeing committee within the University of Warwick. After considering the research design and protocol, full approval (see Appendix 1) was given to the researcher to proceed and data collection commenced.

In the next chapter, the collected data are initially examined for missing values and a number of tests are performed. After that, exploratory and confirmatory factor analyses are performed to test the underlying structure and develop the measurement model, allowing for reliability and validity testing.

5 Initial Results, Data Screening and Model Development

An online questionnaire was administered to collect the empirical data for this study. A sample of 17,754 academic staff members from 27 UK universities was drawn from the population of academic staff members within all UK universities (as explained above). Names, positions, university name, and e-mail addresses were obtained from the universities' websites, as they are publicly available. These were then entered into a database that included all of the information.

Using the Qualtrics professional research suite, the database was imported into the system and invitations were sent to all 17,754 academic staff members. The questionnaire questions are available in Appendix 2. Two follow-ups were sent to staff members who did not participate. Many academic staff members apologised for not being able to respond, attributing their inability to participate to being quite busy and having no free time.

Of the 17,754 surveys sent, a total of 499 respondents completed the survey yielding a **response rate of 2.8%**. Partially completed surveys were ignored due to the fact that most of them did not reach or complete Part 3, where their perceptions would be recorded. All responses were first captured within the Qualtrics online research suite. These were then exported to SPSS, Excel, and SPSS AMOS as needed. Upon completion of the survey, respondents were provided with the information needed to access the free resources (incentives were explained above).

In this chapter, initial results are presented and data screening measures are used to ensure accuracy and usefulness of the data. After that, an exploratory factor analysis is carried out to investigate the underlying structure. This also allows for reliability and validity testing of the model. Then, a confirmatory factor analysis is carried out and the measurement model is developed. Reliability and validity tests are also revisited during the confirmatory factor analysis stage.

Lastly, a number of multivariate assumptions are examined, to ensure that structural equation modeling assumptions are not violated.

5.1 Demographics

The following figures show the general profiles of the participants in this study.

5.1.1 Gender

About 61.32% of the respondents are male while the remaining 38.68% are female respondents (Figure 5.1).

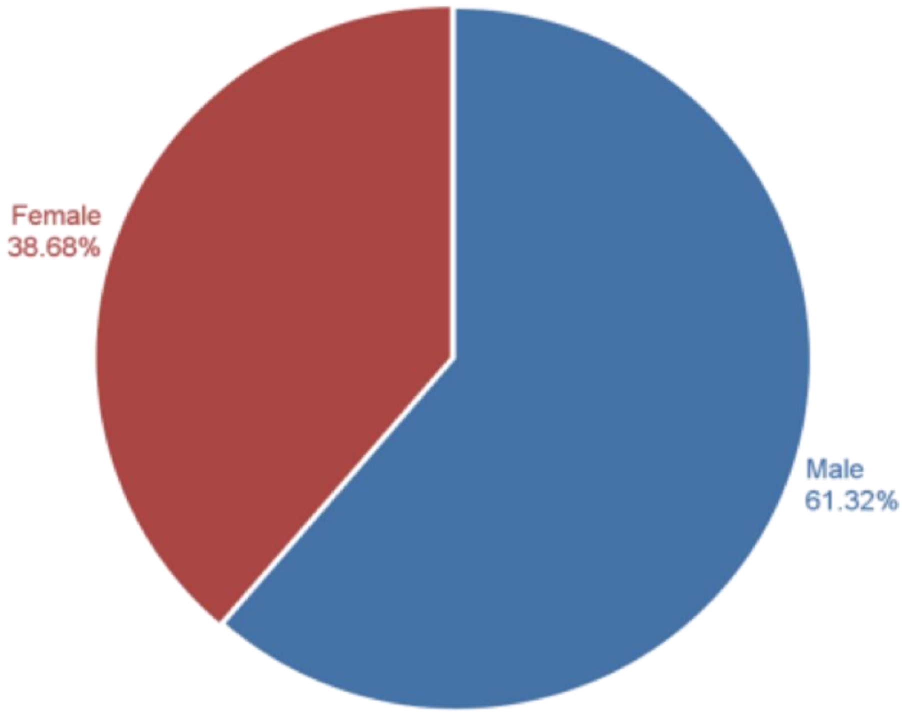

Figure 5.1 Demographics: Gender

5.1.2 Age

In terms of age, most of the respondents are coming from the middle age group (30-50), which contributes to 59.12% of the total respondents. 39.08% of participants are from the older group (over 50 years) while the remaining 1.80% are from the younger group (under 30 years) (Figure 5.2).

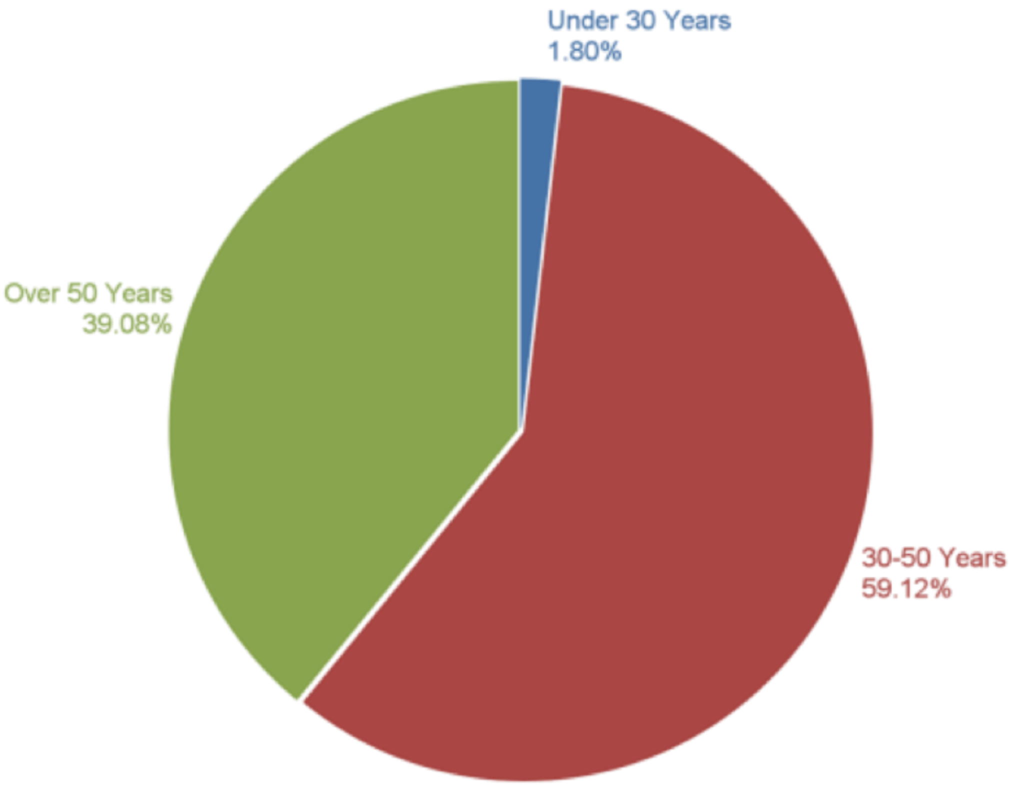

Figure 5.2 Demographics: Age

5.1.3 Experience

Of all respondents, 63.73% have more than 9 years of work experience while 20.84% of respondents have between 5-9 years. The remaining 15.43% of respondents have less than 5 years of experience (Figure 5.3).

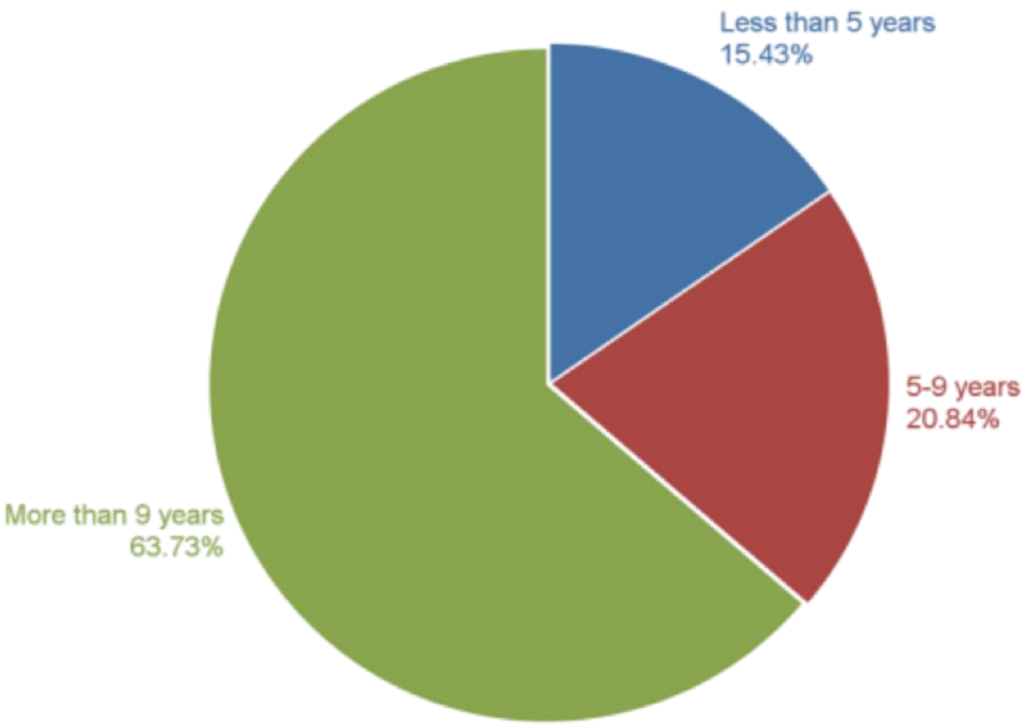

Figure 5.3 Demographics: Work Experience

5.1.4 Country

With regard to the country, 37.27% of respondents are from England, 30.66% from Scotland, 21.44% from Wales, and 10.62% are from Northern Ireland (Figure 5.4).

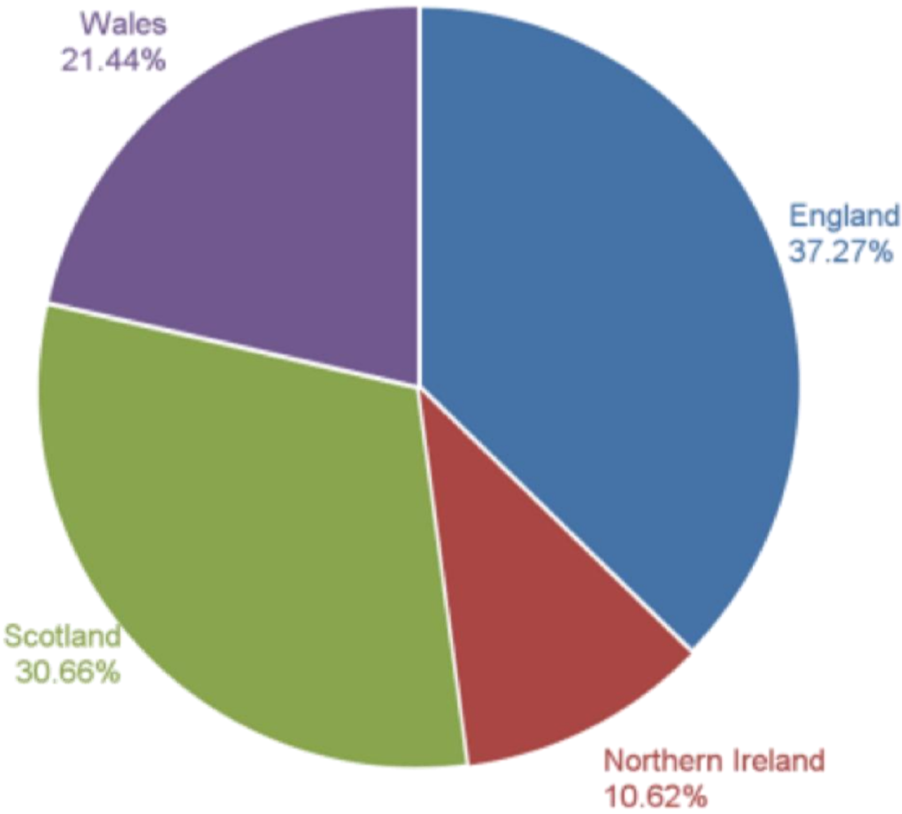

Figure 5.4 Demographics: Country

5.1.5 University

Respondents from over 25 universities participated in the study. Below is a pie chart showing the percentage of participants from each university (Figure 5.5). Despite listing all universities, some chose the “other” option indicating that perhaps some universities were merged or that respondents could not find the name of their institutions.

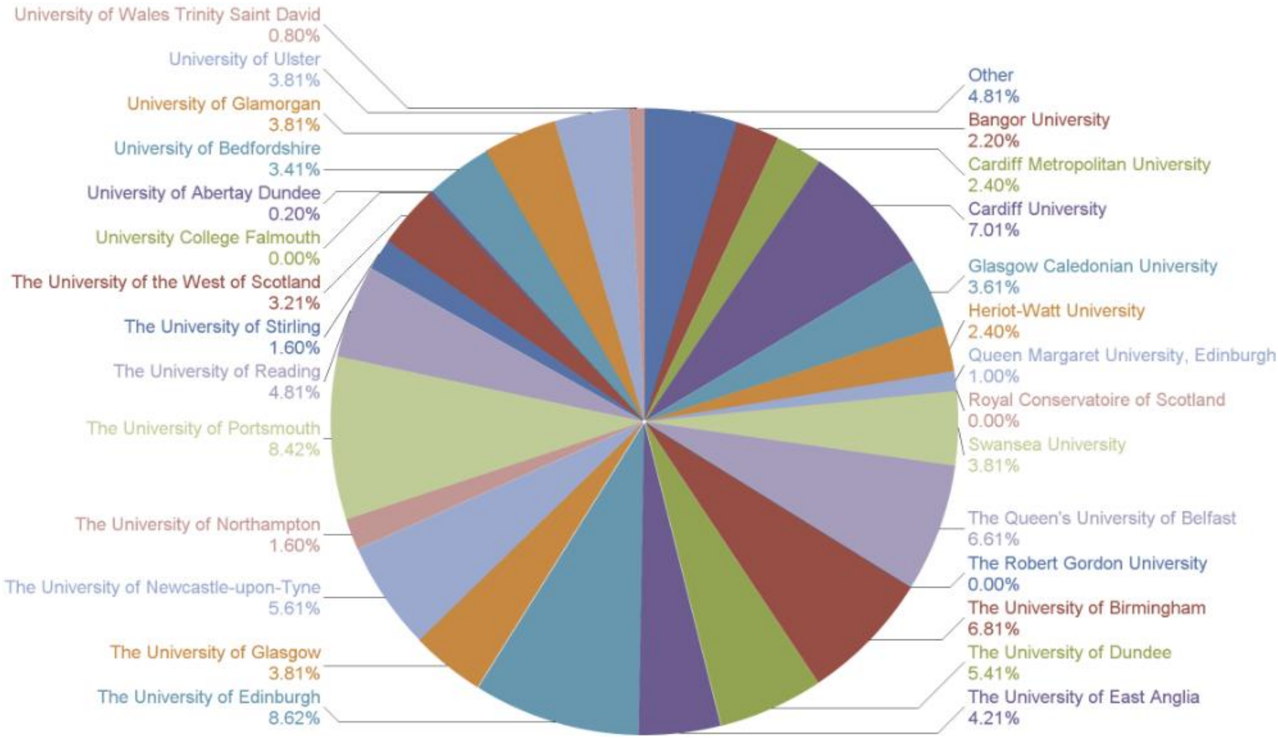

Figure 5.5 Demographics: University

5.1.6 Education

Most respondents (77.75%) had a doctorate degree while 19.04% had masters. The remaining 5.81% had a university diploma or a bachelor degree while 2.4% had other degrees or qualifications (Figure 5.6).

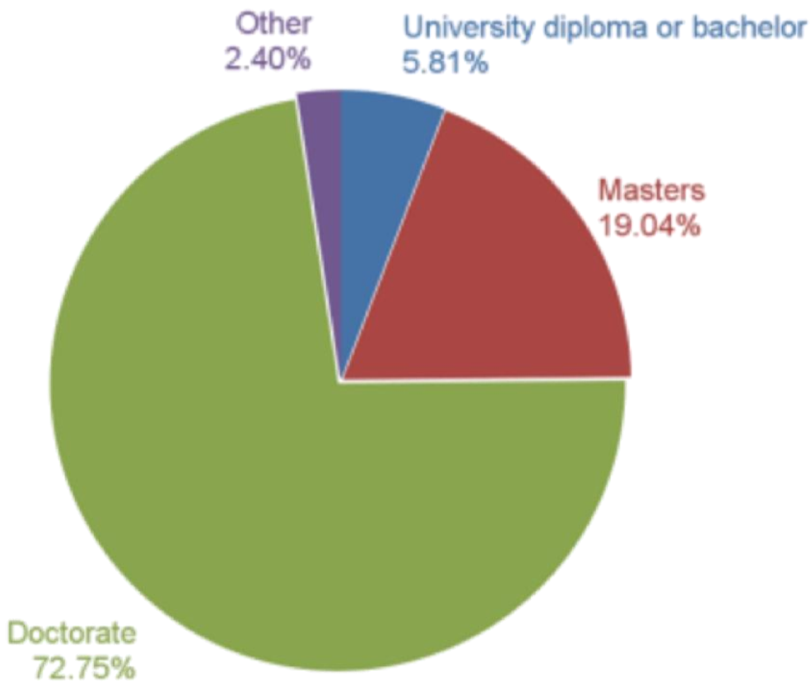

Figure 5.6 Demographics: Level of Education

5.1.7 Number of Teaching Hours

The majority of respondents (67.54%) are dedicating 51-500 hours/year to teaching and teaching-related activities. 17.03% of respondents indicated that they are dedicating 501-1000 hours/year on teaching and teaching-related activities. The other 12.22% are dedicating 50 hours/year while another 3.21% are dedicating more than 1000 hours/year. Those dedicating less than 50 hours/year are likely to be researchers with low teaching loads or part-time staff (Figure 5.7).

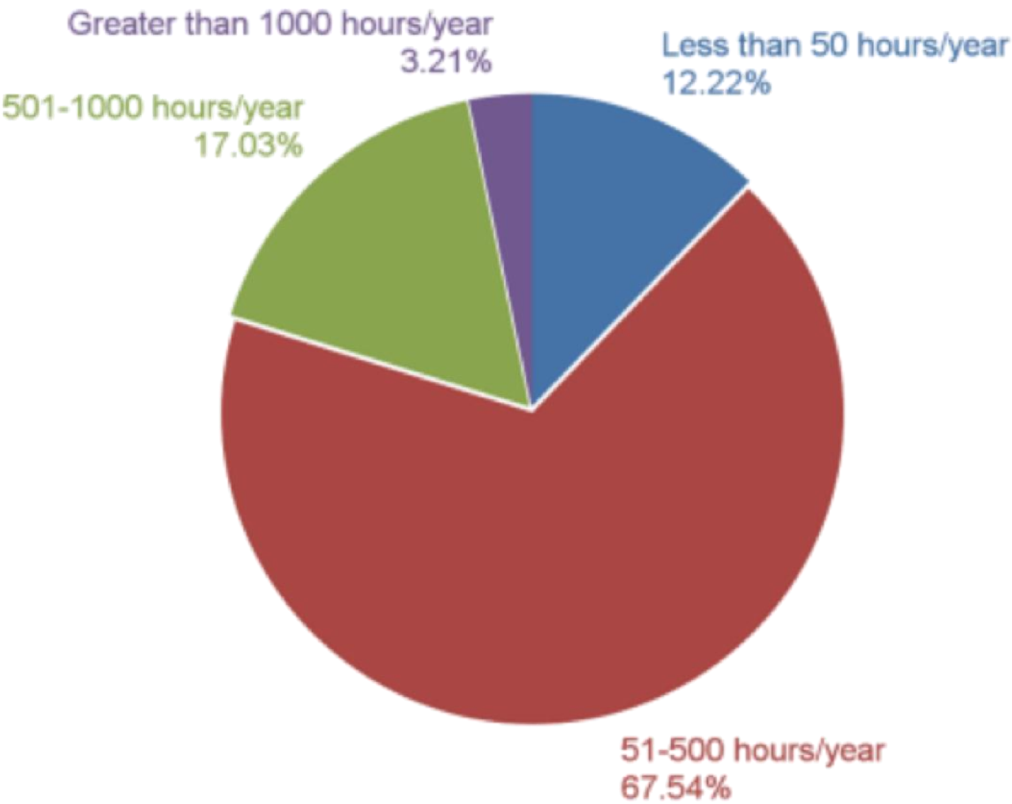

Figure 5.7 Demographics: Number of Teaching Hours

5.1.8 Adopters and Non-Adopters

The majority of respondents (91.18%) indicated that they have adopted some form of learning or educational innovations. The remainder (8.82%) of respondents indicated that they have not (Figure 5.8).

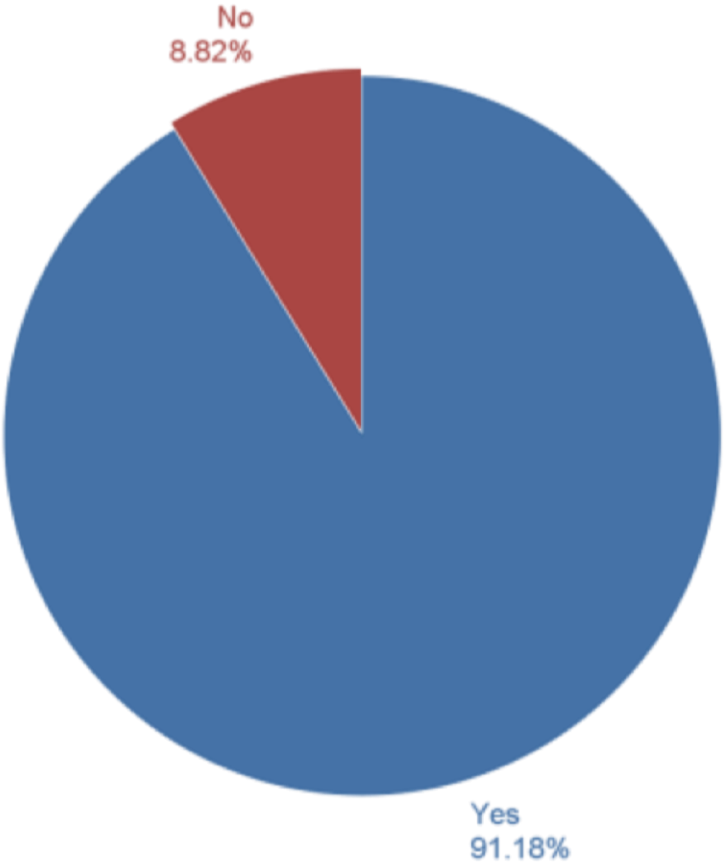

Figure 5.8 Demographics: Adopters and Non-adopters

5.1.8.1 Reasons for Adoption or Non-Adoption

Respondents who have indicated adopting some learning innovation in the past were asked to explain briefly why they did so. Similarly, respondents who indicated not using any learning innovation were asked to explain the reasons behind their hesitation.

Among the many reasons respondents gave for using learning innovations, the researcher aggregated and combined similar answers. Answers were then categorised into staff or students reasons. Reasons in bold are most common among answers:

Staff related reasons:

- Make teaching efficient due to staffing cutbacks.
- Ease of use (of the innovation they used).
- Making my life easier.
- **Job benefits** (Reduction of work load, time savings such as reducing contact time, improving job performance such as enhancing teaching, flexibility, efficiency, ease of communication)
- Makes my job interesting.
- **Testing new things.**
- Follow best practice.
- **Peer influence** (e.g. Good results demonstrated by colleagues or discussions).

Students related reasons:

- Encourage independent learning.
- **Improve students' learning.**
- **Improve students' experience**.
- Meet students' expectations.
- Improve employability for students.
- **Improving students' engagement.**
- Make learning more accessible (e.g. Delivery to larger groups or overseas meetings).

- Adding interactive elements to enrich students learning.

Moreover, among the reasons respondents gave for not using learning innovations, the researcher aggregated and combined similar answers. Reasons in bold are most common among answers:

- **Lack of time.**
- Distrustful of all innovations and believe they are all rubbish.
- Unfamiliar with technology.
- Lack of confidence.
- Inexperienced or lack the skill.
- Unconvinced of the benefits.
- New role.
- **Lack of awareness or knowledge of tools and approaches available**.
- Not needed.
- Lack of departmental or university incentives and encouragement.

5.1.9 Voluntary or Mandatory Adoption

The majority of respondents (73.17%) indicated that they have adopted innovations out of their own free well. The remainder (26.83%) of respondents indicated that they were asked to do so (e.g. Use was mandated) (Figure 5.9).

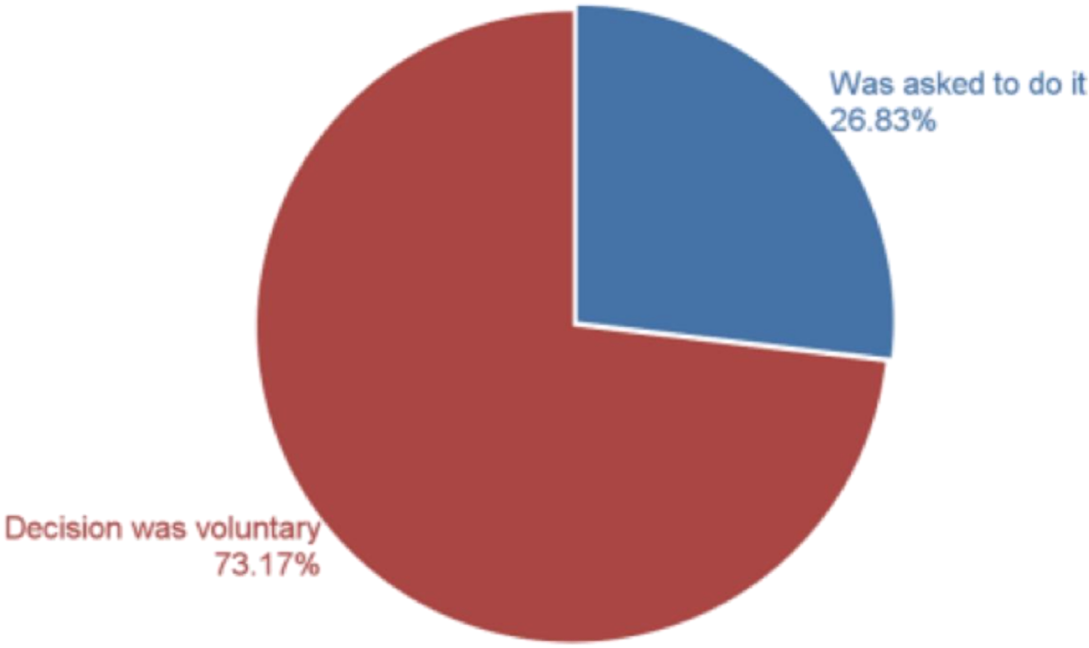

Figure 5.9 Demographics: Voluntary of Adoption

5.1.10 Experience Using Innovation in-question

Respondents who indicated using some learning innovation in the past (or present) were asked to indicate how long they have been using it. 43.14% of respondents indicated that they have between 2-5 years of experience using the particular learning innovation in question. The other 30.09% indicated that they have only been using it for less than 2 years while the remaining 26.77% indicated using it for more than 5 years (Figure 5.10).

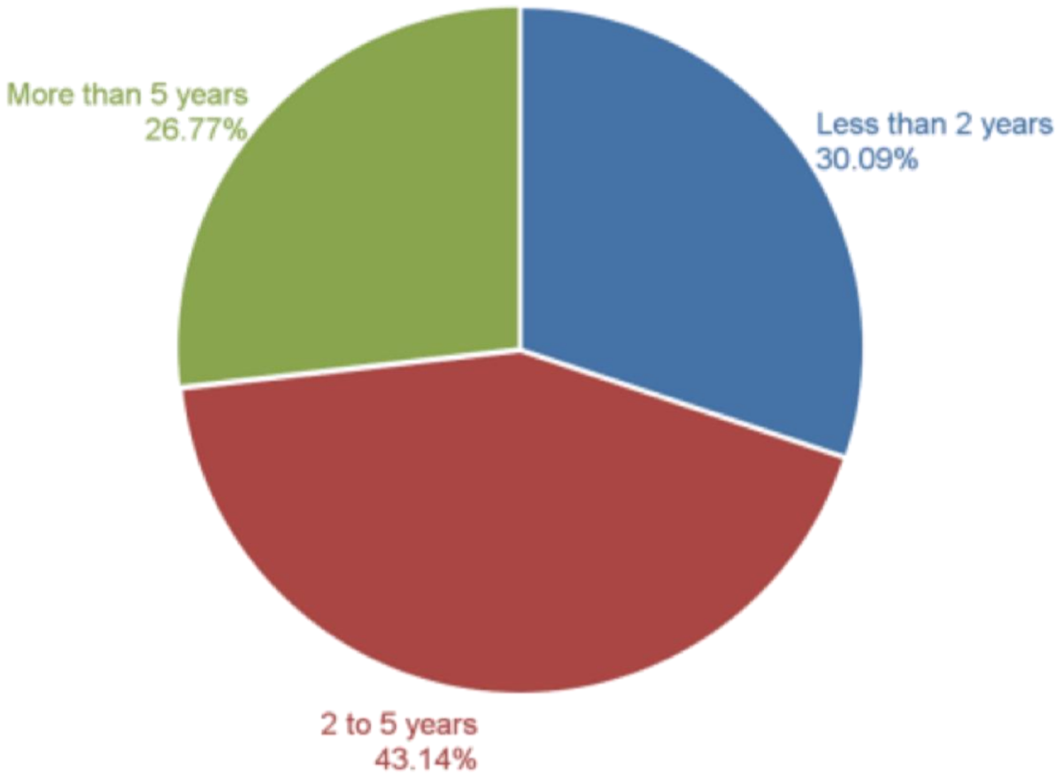

Figure 5.10 Demographics: Experience using Innovation

5.2 Descriptive Statistics

The following table reports means (averages of the responses on the 7 point Likert scale) and standard deviations for all items since it is good practice to report them in studies using structural equation modeling (SEM):

	Mean	Std. Deviation
Performance Expectancy		
-I would find that using a learning innovation is useful in my job	5.99	1.101
-Using a learning innovation would enable me to accomplish tasks more quickly	4.84	1.466
-Using a learning innovation would increase my productivity.	4.78	1.456
-Using a learning innovation would make it easier for me to do my job.	4.89	1.457
Effort Expectancy		
-Learning to use the learning innovation must be easy.	5.16	1.482
-I would find the learning innovation easy to use.	5.11	1.209
-The approach to use the learning innovation must be clear and understandable to me.	6.01	1.008
-It would be easy to become skilful at using a learning innovation.	4.99	1.246
-The use of the learning innovation does not take much effort.	3.97	1.615
-The use of the learning innovation does not require too much time.	3.85	1.695
Social Influence		

-People who influence my behaviour think that I should use the learning innovation.	4.37	1.472
-People who are important to me think that I should use the learning innovation.	4.41	1.434
-I would use the learning innovation because of the proportion of co-workers who use it.	3.73	1.618
-The senior management would be helpful in the use of the learning innovation.	3.91	1.571
-The organization has supported the use of the learning innovation.	5.15	1.381
-Using the learning innovation would improve my image within the organization.	4.71	1.295
-People in my organization who use the learning innovation have more prestige than those who do not.	3.87	1.408
Facilitating Conditions		
-I have control over using any learning innovation I see fit.	4.94	1.498
-I have the resources necessary to use the learning innovation I see fit.	4.57	1.456
-I have the knowledge necessary to use the learning innovation I see fit.	4.77	1.467
-Guidance is available to me for the selection of the appropriate learning innovation that I could use.	4.73	1.376
Results Demonstrability		
-The results of using the learning innovation by myself or others are clear to me.	5.15	1.319
-I would have no difficulty in telling others about	5.55	1.243

the results of the learning innovation I use.		
-I believe I could communicate to others the consequences of using the learning innovation	5.59	1.174
Visibility		
-I have seen what others are doing with the learning innovations they are using.	4.76	1.417
-Learning innovations are not very visible in my organization.	3.80	1.514
-It is easy for me to observe others using learning innovations in my organisation.	3.98	1.430
-Effective learning innovations in my organization are disseminated for others to learn from.	4.31	1.457
Trialability		
-I've had a great deal of opportunities to try various learning innovations.	4.14	1.535
-I know exactly what I can do If I wanted to try out a learning innovation.	4.26	1.515
-The ability to try a learning innovation before using it is important to me.	5.63	1.180
-I am likely to use learning innovations that have been tested and proven effective by others in my area.	5.21	1.288
-I am likely to use learning innovations tested and proved to be effective by myself.	5.91	1.039
Reinvention		
-It must be easy to change the learning innovation I would use to do what I want it to do.	5.39	1.182
-I am more inclined to use a learning innovation that I am able to change or adjust to suit my	5.89	.933

needs.		
-I am more likely to adopt and use a learning innovation when I am actively involved in customizing it to fit my unique situation.	5.59	1.056
Students' Requirements and Expectations		
-Before deciding to use a learning innovation, it must be clear how it can help me meet or exceed my students' expectations.	5.91	1.004
-Knowing about my students' requirements allows me to use an appropriate learning innovation.	5.95	.922
-Using a learning innovation helps me meet or exceed my students' expectations.	5.46	1.161
-The choice of what learning innovation I use is not dependent on whether it can help me fulfil my students' requirements or not.	3.30	1.702
Students' Learning		
-Before deciding to use a learning innovation, it must be clear how it can improve students' learning.	5.90	.943
-The learning innovation I use must help improve students' learning.	5.97	.985
-Understanding how my students learn best will help me to use the appropriate learning innovation.	5.92	.968
-I evaluate the learning innovation I use to ensure that it enhances my students' learning.	5.62	1.173
Behavioural Intention		
-I intend to use a learning innovation in the near	5.59	1.224

future.		
-I predict I would use a learning innovation in the near future.	5.70	1.169
-I plan to use a learning innovation in the near future.	5.55	1.280

Table 5.1 Means and Standard Deviations

5.3 The Analysis and Statistical Procedure

Data collected underwent a screening process consisting of many steps, to ensure that subsequent analysis is based on a complete dataset that is void of any issues such as incomplete or unengaged answers.

Descriptive and reliability statistics were implemented using SPSS version 21 while for the reporting of charts and similar illustrations Qualtrics, Microsoft Excel, or SPSS AMOS were used.

Furthermore, to ensure that the data used are reliable and valid, the analysis of the data consists of a number of stages:

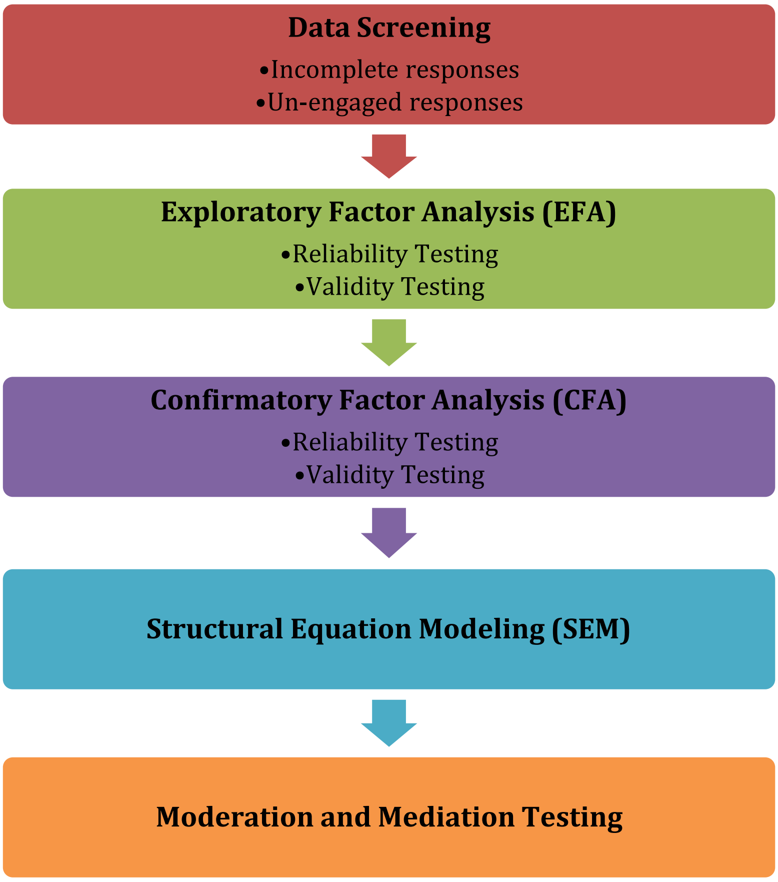

Figure 5.11 Analysis and Statistical Procedure

In the first stage, an exploratory factor analysis (EFA) was run as an initial step to investigate the loading of the different factors and whether the items used are measuring what they are theoretically supposed to measure. At this stage, reliability and validity of the model was investigated.

In the second stage, a confirmatory factor analysis (CFA) was run to further investigate the measurement model and the validity and reliability of the measures. Items with issues such as low loadings were candidates for removal as this could improve the model and reduce discrepancies.

In the third stage, data collected was analysed using the structural equation modeling (SEM) approach. SEM was applied to investigate the structural model and test possible relationships between the different components of the model.

In the fourth stage, moderation and mediation effects were assessed. This allowed for a better understanding of how the different constructs may act or perform differently in different situations or under different conditions.

5.4 Data Screening

Prior to analysing the data, there was a need to do some screening, cleaning, and preparation of the data to ensure that the data that will be analysed are accurate and of value. Therefore, as part of the screening process, the researcher checked the data for: missing values, unengaged responses, outliers, and kurtosis. While these checks were done prior to analysing the data, further steps were also taken later.

5.4.1 Missing Values

To ensure that there were no empty responses on important questions such as the constructs used in the model, a response was mandatory for such questions. However, there were some partially completed responses where participants did not come back to complete the survey and these were deleted.

5.4.2 Unengaged Responses

The researcher looked at the degree of engagement of respondents and two cases were removed as they had a standard deviation value lower than 0.3 for the range of constructs as a whole showing very unengaged responses that would not be of any use when predicting or studying variances as responses did not have any variance.

5.4.3 Outliers

One of the advantages of using multiple answer questions rather than allowing text input is to reduce participants' error such as entering incorrect or inaccurate data.

Moreover, as most part of the questionnaire uses a Likert scale type of questions, outliers would have a lower chance of occurring as the user selects from pre-entered options. This is also the same for other multiple-option questions such as age, education, and work experience where the options were pre-entered as categories.

That being said, outliers may also occur as a result of some differences between certain groups of participants. Since the data were collected across different universities and countries, outliers may surface later when investigating the measurement or structural model.

5.4.4 Kurtosis

The researcher carried out a kurtosis test using SPSS on the constructs as well as demographics data (Age, Education, Gender, Years of experience) to investigate possible questions that may have been answered very similarly by most respondents; therefore, having little variances. The following table shows the constructs that had little variances (see Appendix 3 for variables lookup tables):

	PE_1	EE_3	RD_3	T_5	SRE_1	SRE_2	SL_1	SL_2	SL_3	BI_2
Kurtosis	4.129	3.53	2.251	3.214	4.779	4.944	2.303	2.828	3.751	2.349

Table 5.2 Data screening: Kurtosis

The point of running such test is to keep an eye on these values in case they cause any problems or issues during the exploratory factor analysis (EFA) stage. For instance, they may have low commonality values or not load on any factor.

5.5 Homogeneity Test of Adopters/Non-Adopters

Since the study is capturing perceptions of adopters and non-adopters, it is best to initially test whether there are significant differences between both groups with regard to how they answered the survey (i.e. their perceptions). Such investigation would help the researcher in understanding, at this early stage, whether to expect significant differences in answers. Another similar test (Invariance test) will be carried out later in this chapter, as part of the process followed to prepare the structural model.

One possible way to explore the homogeneity of variances is through the use of Levene's test of the homogeneity of variance and ANOVA. Leven's test tests the hypothesis (H_0) that variances are equal between both groups being examined (Field, 2009). If the result of the test is significant, we reject the null hypothesis because we would have enough evidence to reject it. In such case, this would indicate that both groups being examined are significantly different and that the assumption of homogeneity is violated.

Appendix 4 shows the SPSS output of the calculated test for all the items used to measure the constructs for both adopters and non-adopters. From both the Test of Homogeneity of Variances and the ANOVA tables, it can be seen that there are significant values indicating significant differences between adopters and non-adopters.

Two additional tests (Welch and Brown-Forsythe) were also calculated for confirmation purposes as they are both robust when there is violation of the homogeneity of variance (Field, 2009). Results are also presented in Appendix 4, in the third table: Robust Tests of Equality of Means. The results clearly show that some values are significant, indicating that the variances are significantly different between adopters and non-adopters (Field, 2009).

These results give a clear indication that there are significant differences between adopters and non-adopters and this should be taken into consideration in the next stage. To be specific, there is a need to be aware of this when developing the structural model, to ensure that the model proposed by this study is optimised or explains adoption intention for both groups if possible.

5.6 Exploratory Factor Analysis (EFA)

As a result of the data screening procedure outlined above the number of cases to be considered in this study was reduced (n:497). Now that data screening is done, the next step was to carry out an exploratory factor analysis (EFA).

EFA enables the investigation of possible underlying structures behind correlations between different factors (Brace, Kemp, & Snelgar, 2012). Using SPSS, EFA can be run using data of measurement level that is ratio, interval, or ordinal.

The researcher carried out an EFA using a maximum likelihood extraction method and a Promax rotation method since it is expected that there will be correlations between constructs of this study and the dataset is large (Brace et al., 2012; Hair et al., 2010). Maximum likelihood estimation is used to determine unique variance and correlations, but more importantly also, it is used to be consistent with the subsequent confirmatory factor analysis (CFA) stage.

Instead of allowing SPSS to explore and define the number of factors from the data (i.e. using the Eigenvalue option), the researcher defined the number of factors since the researcher already had a priori theory (Hair et al., 2010) where the model consists of 11 factors to be tested. Allowing the software to uncover the number of factors is more appropriate if the theory was not clear or the researcher is not sure about the underlying structure.

After assessing the resulting model and dropping items that were not loading to remedy problems as suggested by Hair et al. (2010), the resulting EFA (see Appendix 5) had a KMO value of .824 which is above the acceptable value of .7 keeping in mind that the closer the value to 1 the better (Brace et al., 2012). Lookup tables of the variables used are reported in Appendix 3.

Commonalities for each variable were sufficiently high (all above 0.300 and most above 0.500). The reproduced matrix had only 2% non-redundant residuals greater than 0.05, further confirming the adequacy of the variables and the model. Total variance explained was 65% which is considered to be very good. The Goodness-of-fit (GOF) shows a non-significant value of .000 which is expected as Chi-Square relies on the sample size, and in this case it is somewhat large (n:497).

As can be seen in Appendix 5, the researcher encountered a Heywood case (un-expected outcome or value is reported by the software) with PE_3's estimate being > 1. In this case for instance, the estimate should have a maximum value of 1. Aside from a few mentions of this possible strange behaviour by some researchers (e.g. Hoyle, 2012; Kenny, 2014; Kline, 2012), not much is found of this Heywood case and why some software packages report such unexpected values. The researcher will keep this in mind in case further issues were caused by this item in subsequent stages.

5.6.1 Issues in Factor Loadings

There were some issues in factor loadings, these are discussed below.

5.6.1.1 Social Influence and Social Image

Interestingly, although SI_4 and SI_5 had a very acceptable communality value initially, after some adjustments to the model they stopped loading. Social influence was already loading on two different factors and still does. However, it seems that social influence was actually loading into two different factors because it could be measuring two slightly different concepts: Social Influence and Image. Looking at both questions SI_4 and SI_5 (see Appendix 2 the Social Influence section), it can be seen that none of those perhaps would fall clearly and directly under either the social influence or the image factor. Hence, this is likely the reason why both of them were not loading.

Additionally, SI_3, although could be considered an item that measures some sort of influence had a low loading. This could be because the item was not actually measuring the influence as strongly as others or because participants who are members of staff would not really be influenced to adopt a learning innovation just because someone else is using it, especially since traditionally, academic members of staff have a higher level of autonomy and freedom. That being said, there is an opportunity to test the loading of SI_3 when producing the measurement model in the confirmatory factor analysis (CFA) stage next, to see if it actually helps in achieving a better model or not.

The development of the social influence construct shows that it actually incorporates measures from a number of similar concepts (Venkatesh et al., 2003) including: subjective norm, social factors, and image. Furthermore, some researchers (Lakhal et al., 2013; e.g. Martins & Kellermanns, 2004) have actually suggested that social influence should not be studied as a single measure. Therefore, it is not strange to experience such split loadings. After all, they could possibly be different concepts and it may be more accurate to measure and test them separately.

5.6.1.2 Trialability

When exploring the pattern matrix (Appendix 5) as part of the initial EFA, Trialability continues to load strongly on the same factor as facilitating conditions. Additionally, trialability seems to be loading on a second factor, visibility, although the loading is low (.355).

One possible explanation behind trialability loading with facilitating conditions is that individuals would probably feel that they are free to try innovations before fully implementing them, therefore, having the freedom to do so. This, in itself, falls under the definition given for facilitating conditions (see Venkatesh, Morris, Davis, et al., 2003) as individuals would feel less constrained.

5.6.2 Reliability and Validity

One possible approach to ensuring the minimum level of measurement error is to investigate properties of the measures that were developed to gain confidence that they are doing their job properly (Field, 2009). Two important properties of measures to investigate are validity and reliability.

After the EFA presented above, a number of reliability and validity tests were run; to ensure that the instrument used to collect the data is reliable and that the data can be used.

5.6.2.1 Reliability Testing

To ensure the reliability of the measures used in this study, Cronbach's alpha values for construct items were investigated (see Appendix 5). All constructs had Cronbach's alpha values well above the cut-off point of 0.7.

5.6.2.2 Validity Testing

Two types of construct validity were investigated: convergent validity and discriminant validity. Convergent validity indicates the degree to which items that theoretically belong to a single construct should correlate highly. On the other hand, discriminant validity indicates the degree to which items or measures of a scale do not measure other constructs.

5.6.2.2.1 Convergent Validity

Based on the pattern matrix produced (see Appendix 5), it can be seen that the following constructs have shown good convergent validity as a result of measures belonging to the same factor loading together: BI, EE, PE, FC, V, SL, RD, ReInv, SRE and SL. All loadings were above the suggested minimum threshold of 0.350 (Hair et al., 2010).

Additionally despite the fact that T was loading on two factors, its loading with FC is showing high convergent validity. Meaning, it is possible that it is strongly related to FC.

Moreover, since the researcher is looking at social image as two different constructs now: SIINF and SIIMG, to differentiate between the two factors it is loading on, both of them show high loadings confirming their convergent validity.

5.6.2.2.2 Discriminant Validity

Based on the pattern matrix produced (Appendix 5), aside from measures related to T which are cross loading, discriminant validity is shown since measures of the same factor are not loading on other factors. Additionally, investigating the factor correlation matrix (Appendix 5) show that there are no correlations higher than .7 between any of the constructs. This confirms the discriminant validity of all the constructs.

5.7 Measurement Model (Confirmatory Factor Analysis)

The EFA carried out by the researcher in the previous section helped the researcher in reaching a base model explaining which measures are related and which are not. Using this knowledge, the researcher then proceeded to develop and assess the measurement model. The measurement model represents a confirmatory factor analysis (CFA) of scales used in this study. This is done to assess how well measurement items reflect the latent variables they are explaining (Byrne, 2010).

When doing a CFA, the validity and reliability of the various factors in measurement model can be examined. This is a necessary step to be taken prior to developing the structural model of this study in the next chapter. Otherwise, we cannot be sure that items are measuring what they are supposed to measure accurately and reliably.

In this study, indicators used were initially defined a priori based on the literature review and were then evaluated as part of the EFA carried out in the previous section. However, it is important to note the difference between observed and latent variables. Observed variables are those that were captured using the data collection instrument while latent factors, on the other hand, are factors that cannot be captured directly, but instead, we use observed variables to reflect them (Kline, 2012). For instance, items related to a construct are considered observed variables while the construct itself is referred to as a latent variable or construct.

When evaluating the measurement model, there are a number of goodness-of-it (GOF) indices that can be used to measure how well the actual data collected (observed variables) matches the estimated covariance matrices (theoretical data) (Byrne, 2010). There are a number of various indices used in the structural equation modeling literature each with varying acceptable thresholds. In this study, the author relied on a number of model-fit indices and their thresholds, as discussed by Hair et al. (2010). There is no need report all GOF indices as many of them are similar and doing so would be of little use.

5.7.1 Initial CFA

Using the items proposed from the final EFA model, the following initial CFA model (Figure 5.12) was created using the SPSS AMOS software. The oval shaped items on the left represent the various factors (see Appendix 3 for variables lookup tables), also known as latent variables or unobserved variables. Co-variances between each of these factors are also drawn and the values are reported on the left side of the diagram. Each factor is represented by a number of measured variables or indicators designated by a box. These measured variables were captured in the questionnaire used by this study. Factor loadings for measured variables are also reported (the line between the oval and box). Lastly, each measured variable has an error variance that is estimated by the software package.

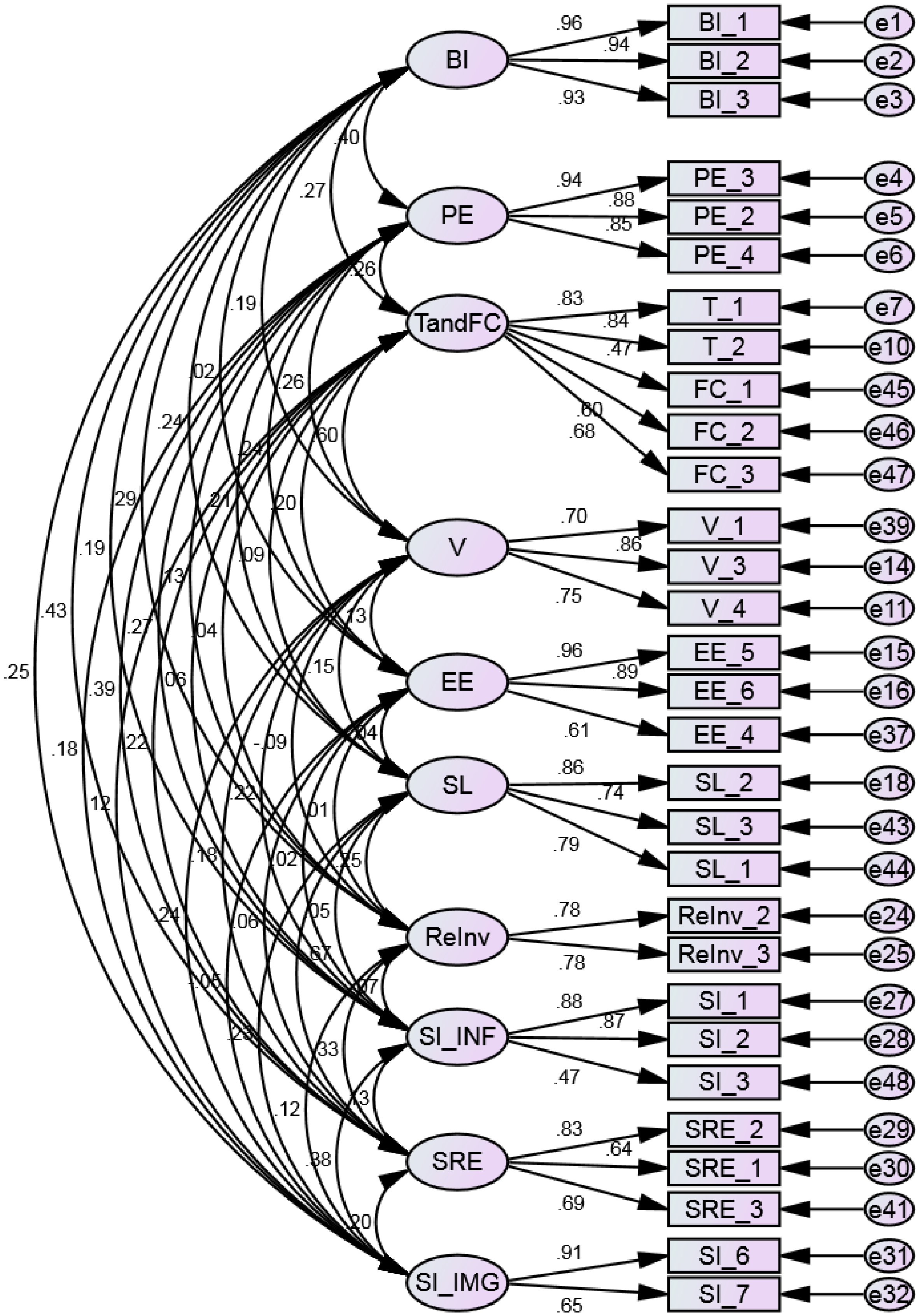

Figure 5.12 Hybrid CFA Initial

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	2.855	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.866	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.829	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.915	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.763	Recommended to be above 0.8
PCLOSE:	.000	Recommended to be above 0.05
RMSEA:	.061	Recommended to be less than 0.1 Better if less than 0.05

Table 5.3 Hybrid CFA Initial GOF

It is important to note that with a large sample (>250 or so), it is quite difficult to obtain optimum goodness of fit parameters values especially if the model is complex. Furthermore, the chi-square test (p-value above) is also influenced by the sample size (Byrne, 2010; Hox & Bechger, 2007; Iacobucci, 2010). Similarly, GFI and AGFI may also be influenced by the sample size (Byrne, 2010).

5.7.2 CFA: Modification and Improvements

There was plenty of room to improve the model fit and it is not unusual that the model-fit process goes through different iterations or tests until a better model is achieved. Moreover, it is well known that CFA can be used both in an exploratory or confirmatory way (Byrne, 2010). Meaning, CFA can be used in a confirmatory way to confirm relationships between constructs already defined, but also, especially if the initial model was rejected by the researcher, it can be used in an exploratory way to test possible relationships by incorporating and exploring the effects of various constructs (Byrne, 2010).

For instance, a number of factors that had lower loading in the previous EFA stage were tested here as well. Most notably, PE_4 was not loading previously. However, once tested in the CFA, it showed a high loading of .85. Moreover, SI_3, which had a low loading in the EFA had a high loading too. However, as can be seen in the initial CFA measurement model above, it caused SI_2 to load much lower and the researcher had to intervene. Therefore, the researcher tested both cases where SI_1 was added with either SI_2 or SI_3. The highest loading of both factors occurred when SI_1 and SI_2 were used. Therefore, SI_3 was dropped in the subsequent model. As can be seen, the process of reaching a better GOF or measurement model can take what can be looked at as an experiential route where various items are tested and removed, etc.

Based on the recommendations put forward by Hair et al. (2010), there are a number of steps that can be taken to improve GOF. First, factors with load loadings can be dropped (Hair et al., 2010). Therefore, the author dropped a number of items to improve the GOF. Ideally, each factor should have a minimum of three items although if some constructs had less than three it would still be acceptable (Iacobucci, 2010).

Another step that can be taken to improve GOF is to introduce new connections as suggested by modification indices (MI) values (Hair et al., 2010). Modification indices are measures for the extent to which the model-fit would be improved if the user accounted for the parameter which is not accounted for. Investigation of the modification indices indicated high covariances values between a number of error terms and one way to resolve such issues is to create covariances between errors that belong to the same factor to account for the parameter. Creation of covariances between error terms relating to the same factor is justified because in many cases, they are systematically correlated (highly related) as they have been worded similarly and people responding to the questionnaire answered them within the same block and they are very close to each other (Byrne, 2010). Therefore, respondents are likely to have answered them similarly.

Furthermore, another step to improving GOF is by investigating residuals for any discrepancies between the proposed model and the estimated model (Byrne, 2010; Hair et al., 2010). SPSS AMOS provides information on residuals on the output report. Items causing a lot of issues (e.g. too many high values) should be removed.

Taking the above steps towards improving the model-fit into account, the researcher was able to reach the following improved model:

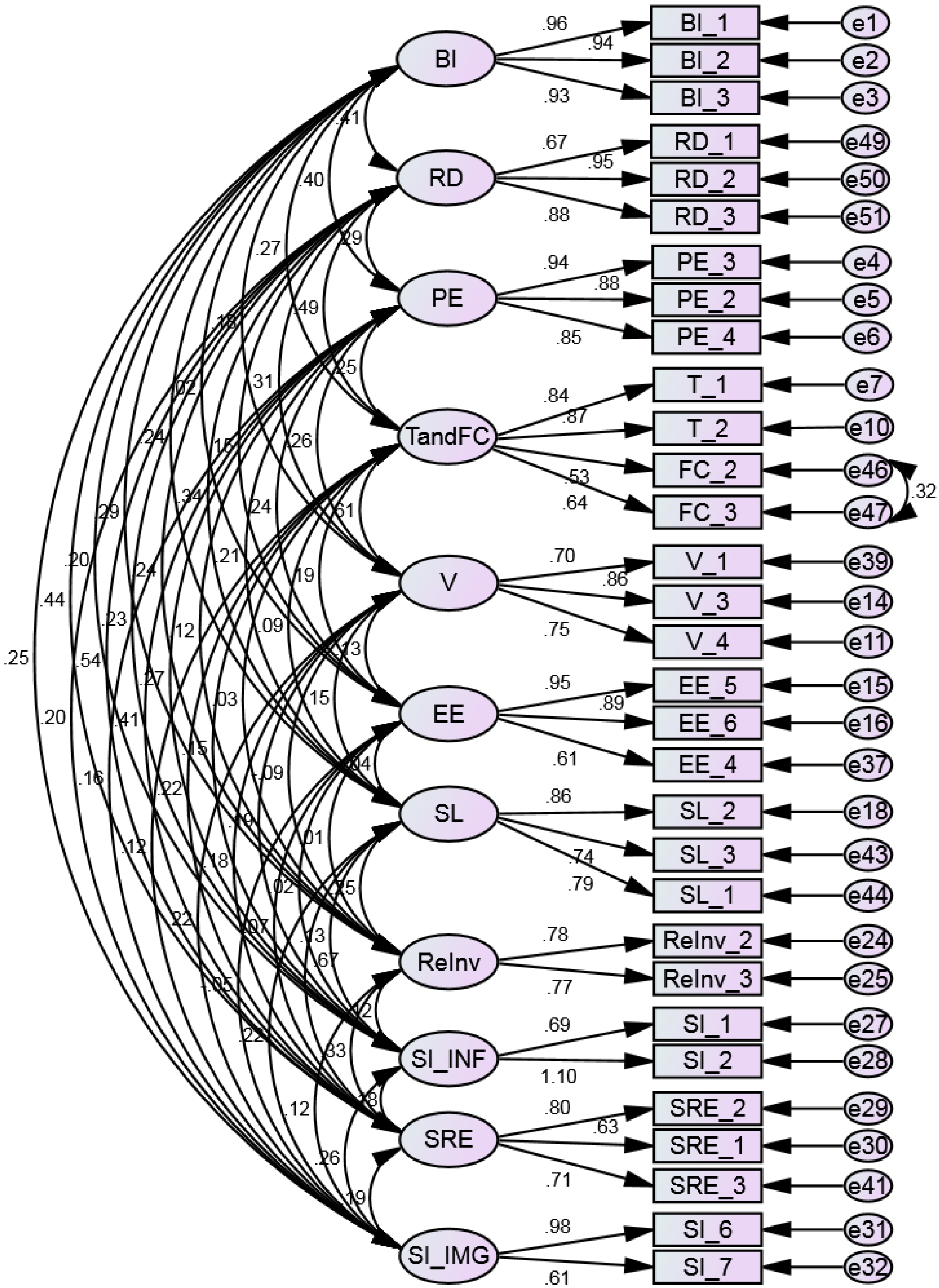

Figure 5.13 Hybrid CFA v1

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	2.566	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.888	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.853	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.936	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.761	Recommended to be above 0.8
PCLOSE:	.010	Recommended to be above 0.05
RMSEA:	.056	Recommended to be less than 0.1. Better if less than 0.05

Table 5.4 Hybrid CFA v1 GOF

As can be seen from the model fit summary above, goodness-of-it (GOF) indices indicate that the model is better than the previous one. GOF indices indicate the degree to which the data fit the proposed model, and in this case and in comparison to the previous model, GOF indices are indicating that this model is fitting the data very well.

Moreover, despite some low loadings, the researcher decided to consider this a better model than the previous one reported above (see 5.7.1). The main reason behind this is that when testing for common method bias and revisiting the reliability and validity of the measurement model next, there will possibly be a need to remove some items. Therefore, it is best to keep as many items as possible while achieving a good model-fit.

5.7.3 Reliability and Validity

Investigating the reliability and validity of the proposed model is important when doing a confirmatory factor analysis (CFA) especially since there are changes (e.g. addition and removal of items) introduced to the model. High reliability is argued to be associated with lower measurement errors (Hair et al., 2010). Additionally, to reflect latent factors properly, observed variables need to show evidence of reliability and validity (Schumacker & Lomax, 2010; Straub et al., 2004).

In this section, the reliability and the validity of the measurement model will be tested.

With the use of the Validity testing tool within the "Stats Tools Package" (Gaskin, 2012) and by imputing AMOS's correlations and standardised regression weights tables into the tool, reliability and validity results are shown in the following table.

	CR	AVE	MSV	ASV	SI_IMG	BI	PE	TandFC	V	EE	SL	ReInv	SI_INF	SRE	RD
SI_IMG	0.785	0.658	0.069	0.037	**0.811**										
BI	0.961	0.891	0.194	0.087	0.248	**0.944**									
PE	0.921	0.796	0.164	0.076	0.165	0.400	**0.892**								
TandFC	0.816	0.535	0.378	0.088	0.119	0.269	0.247	**0.731**							
V	0.815	0.597	0.378	0.074	0.224	0.185	0.261	0.615	**0.772**						
EE	0.868	0.694	0.060	0.014	-0.050	0.024	0.244	0.189	0.128	**0.833**					
SL	0.841	0.639	0.448	0.082	0.218	0.243	0.210	0.090	0.146	0.038	**0.799**				
ReInv	0.752	0.603	0.109	0.037	0.121	0.289	0.124	0.030	-0.089	0.006	0.252	**0.777**			
SI_INF	0.912	0.844	0.075	0.036	0.262	0.196	0.273	0.151	0.190	0.021	0.131	0.123	**0.919**		
SRE	0.760	0.516	0.448	0.136	0.193	0.441	0.405	0.215	0.185	0.066	0.669	0.330	0.176	**0.718**	
RD	0.875	0.705	0.291	0.117	0.205	0.407	0.295	0.492	0.309	0.150	0.338	0.243	0.233	0.539	**0.840**

No Validity Concerns

Table 5.5 Reliability and Validity Testing of the Measurement Model

Note:

- CR (Composite reliability): measures the reliability of the factors and should ideally be above .75.
- AVE (Average Variance Extracted): this is a measure of convergent validity and should be above 0.5 (Hair et al., 2010). Refers to how the items are explaining the factor. It is **shown in the diagonal in bold**.
- MSV (Maximum Shared Squared Variance): the squared maximum variance between the factor and the other factors in the model. Refers to how much of the factor is explained by items outside the factor (i.e. items of other constructs).
- ASV (Average shared squared variance): similar to MSV but takes the average of the squared variances. Refers to how much on average is explained by other items not belonging to the factor itself.
- AVE should always be higher that MSV and ASV; items belonging to the factor itself should explain it better than external items belonging to other factors (Straub et al., 2004).

As shown in the table above, all constructs have a high composite reliability values. High (above 0.50) average variance extracted (AVE) values indicate good convergent validity.

To test for discriminant validity, the researcher compared the square root of average variance extracted (square of AVE) for each construct (diagonal) to all inter-factor correlations (below the values in bold). All factors demonstrated adequate discriminant validity because all diagonal values (square root of AVE) are greater than the correlations.

The above results show convergent and discriminant validity. Therefore, we conclude that adequate reliability and construct validity have been met.

One point to note is that error e28 had a negative variance and the researcher will have to adjust its variance value to .2 as otherwise, it would be negative.

5.7.4 Common Method Bias or Variance

CFA helps in understanding the extent of the common method bias. Common method bias or common method variance is a type of bias that could occur in certain situations when collecting data. In this particular case, since the data was collected using the same instrument, there is a possibility that there could be common method bias. Common method bias remains a threat to validity in Information systems research when using one method and despite the majority of IS research using a single data collection method, only few studies investigated and mentioned it (Straub et al., 2004). Therefore, in this section, the author will investigate whether there are common method bias or common method variance effects.

The test that the researcher will use is the "common method factor" technique for studies that do not measured a common factor explicitly (MacKenzie & Podsakoff, 2012) such as the case in this study.

To investigate for common method bias, the researcher introduced a common latent factor (CLF) to the CFA measurement model (see Appendix 8: Common Method Bias Adjusted Model). However, introducing the CLF introduced an issue where the model cannot run and AMOS outputs the iteration limit reached message. Upon investigating the regression weights, the researcher noted that regression weights for RD items were very high (above one), what is known as a Heywood case (Hoyle, 2012; Kenny, 2014; Kline, 2012). One approach to fixing such an issue is to define the parameter estimate for the items to be the same, 1. However, once that is done, the model ran but a negative error appeared for item SI_1. Therefore, the researcher defined the error term for that item to be .4 (close to the error estimate of the second item for the same construct since they both measure the same thing), so that it doesn't become negative. Some authors discussed possible causes of such illogical values, including the possibility of model specification error or that it is caused by an issue in the sample (e.g. wide differences). In this study, because it is important to ensure that this is not a specification error, we assess discrepancies in section 6.4.2. Goodness of fit indices can also indicate if there are critical issues in the model as they would indicate bad fit. Significant problems or issues in the model can be identified through the examination of these two areas.

The next step, then, was to compare standardised regression weights with and without the CLF. Comparison of both (see Appendix 7) shows some big differences between the regressions weights for both models. Therefore, this indicates there is a common method bias and that a large portion of the variance is being explained by the CLF.

As a result of this finding, the researcher was presented with two options at this stage, drop the affected items and continue without adding the CLF, or, to continue with the CLF added to the hybrid model. Simply dropping the items and continuing would mean that the information captured for these dropped items would be lost. Therefore, the researcher decided to take a more robust approach to deciding which of the two options to take.

First, the researcher would re-check the validity and reliability of the model that has a CLF (I.e. The common method bias adjusted model). If any reliability or validity issues appear, the researcher would try to remedy them. Then, if an acceptable model is reached, it would be compared to the other model (the one without any affected items and with no CLF). Finally, the decision would be made based on the validity and reliability of each model first, and then, based on the GOF parameters and whether there were any issues (.e.g. influences) caused by the CLF.

Reliability and validity tests for the models are presented in Appendix 9 (Model without CLF) and Appendix 8 (Model with CLF).

Reliability and validity testing of the common method bias adjusted model (i.e. the model with CLF) shows a number of reliability and validity concerns (see Appendix 8 for full analysis). These concerns were related to: TandFC, ReInv, SRE, and RD constructs. The researcher attempted to remedy some of these concerns by dropping low loading items for these aforementioned constructs. Unfortunately, this led to further issues. Therefore, the researcher stopped here with regard to this option.

Next, the author dropped the affected items and made some minor adjustments to the model. This resulted in the model without CLF presented in Appendix 9. Then, the reliability and validity of this model was tested and no reliability and validity issues were found.

Based on the above, although common method bias existed and was influencing a number of items, those items were dropped. Common method bias might have occurred and affected these items as a result of some questions affecting how the respondent should respond next (Straub et al., 2004).

As explained before, another approach would have been to keep these items and continue with the analysis while having the CLF. However, the author has tested the model with CLF and it was clear that it had a significant negative effect on the model as well, causing reliability and validity issues. Therefore, for pragmatic reasons, the **following affected constructs and items were dropped**: FC_3 (Item), SI_INF (Construct), and RD (Construct).

In subsequent sections, the study will continue using the final modified model without CLF presented in Appendix 9 and also shown here for reference:

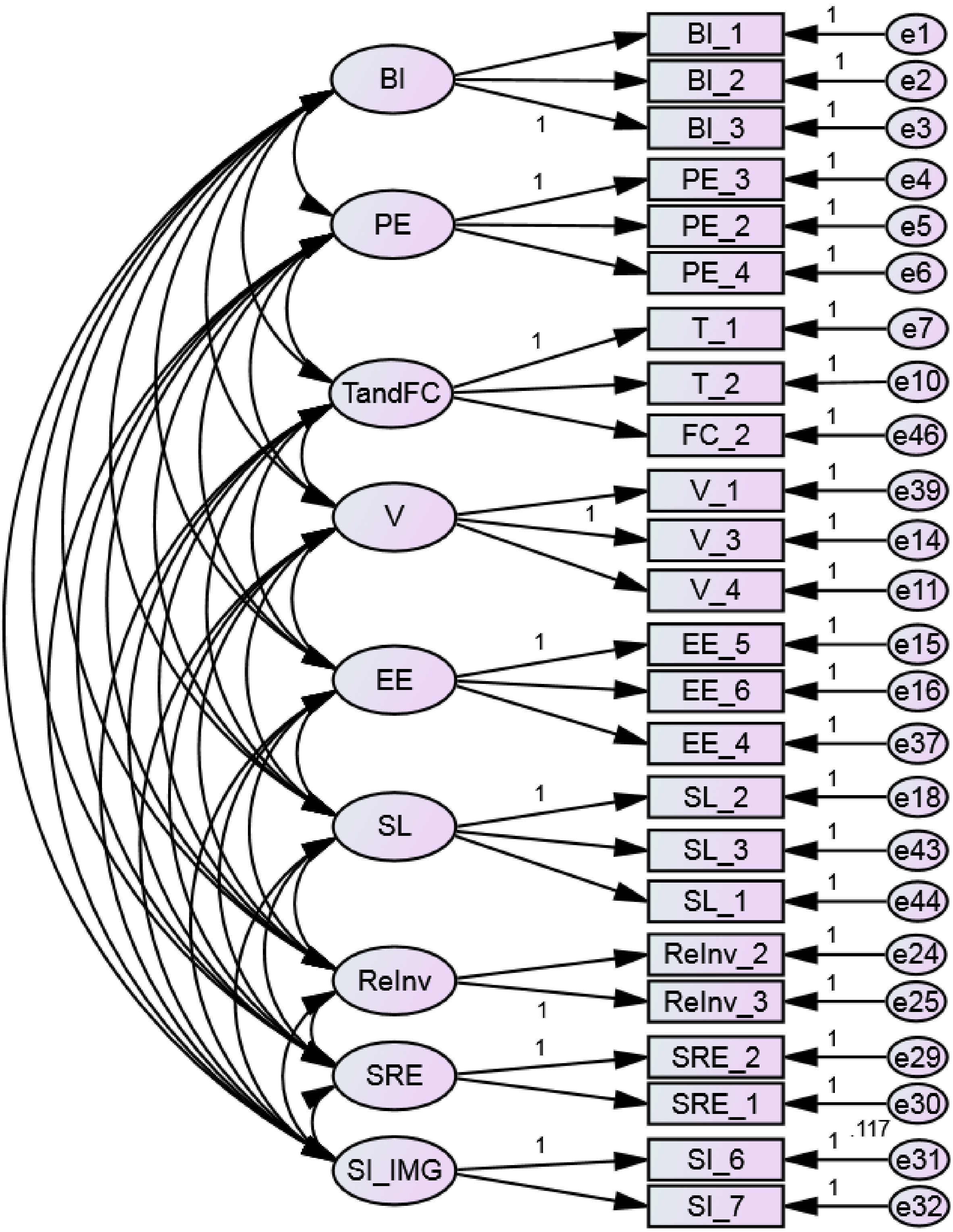

Figure 5.14 Final Modified Model Without CLF

5.7.5 Outliers

Outliers are cases where some values are substantially different from others in the data set.

Using AMOS, the researcher investigated multivariate outliers using the Mahalonobis d-squared values which indicate observations farthest from the centroid (Byrne, 2010). Outliers can affect the model's GOF. However, in this study, the achieved model is very good. Still, the researcher decided to investigate possible outliers, to see if there were any observations considered very far away from the rest of the observations.

A single observation was removed as it had a Mahalanobis d-squared value of over 100.000, over 15.000 in difference to the next observation which had a Mahalanobis d-squared value of 85.917. Therefore, reducing the number of cases (n:496).

5.7.6 Invariance Testing

In an early section, a test of homogeneity was carried out to investigate whether there were significant differences in responses between adopters and non-adopters. The test showed that there are in fact significant differences (5.5 Homogeneity Test of Adopters/Non-Adopters above).

When carrying out research that spans across different groups (i.e. different countries, universities, etc.), it is important to be aware of and reduce any bias that may have resulted from the data collection and/or respondents' characteristics (Cohen et al., 2011). To reduce such bias, there is a need to assess the measurement invariance across different groups (e.g. gender, age, experience, etc.). This is also important as the researcher plans to study moderation effects at a later stage. Hair et al. (2010) recommends establishing some form of metric-invariance prior to examining path estimates.

Following these recommendation, the researcher investigated the measurement model invariance to ensure that the factor structure is equivalent across different groups or values of multi-group moderators. For instance, we want to find out if the factor structure for both men and women are the same. If testing the model across different groups shows good goodness-of-fit (GOF) for the model, this means that we have configural invariance and that the groups are likely to be equivalent. Hence, indicating that the model can be used across different groups.

Moreover, the importance of investigating measurement model invariance rises if the researcher wants to create composite variables. It is useful to create composite variables in complex models as retaining a full hybrid model consisting of the measurement and structural models can be too difficult to work with especially if there are plans to test moderators, mediators and similar affects.

One approach to test that the model is invariant is to look at the GOF parameters for the calculated model after defining a number of groups within AMOS. If the GOF parameters were good, this indicates that the model is equivalent across different groups.

Using AMOS, the following groups were created using categorical data captured in the survey to test the model across: Gender (Male/Female), Age (30-50 Years/Over 50 Years), Education (MSc/Doctorate), Number of teaching hours per year (51-100, 501-1000), Experience (Medium/High), and country (England/Scotland/Wales).

Those groups were chosen as they had somewhat an appropriate number of cases of close to or above 100, as otherwise, if the number of cases is low, the model will not run. Total number of observations or cases used (n) is 496.

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	1.587	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
CFI:	.956	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.748	Recommended to be above 0.8
PCLOSE:	1.000	Recommended to be above 0.05
RMSEA:	.014	Recommended to be less than 0.1 Better if less than 0.05

Table 5.6 GOF for Multigroup Invariance Testing

Based on the very good parameters achieved above, we can say that the model is equivalent across different groups.

In addition to the above test and to confirm these findings, a chi-square test of difference will be used. This test was also done using AMOS and the Stats Tools Package (Gaskin, 2012) which helps in comparing Chi-square and degree of freedom values for unconstrained and fully constrained models. In the fully constrained model, regression values are removed from the lines and variances for factors are restricted to 1.

The researcher ran the chi-square difference test using the groups mentioned above to ensure that the model is equivalent across different groups at the model level. The output from comparing both the constrained and unconstrained model is:

	Chi-square	df	p-val	Invariant?
Overall Model				
Unconstrained	4514.773	2808		
Fully constrained	4809.096	3096		
Number of groups		13		
Difference	294.323	288	0.386	YES

Table 5.7 Invariance testing of the fully constrained and unconstrained model

As can be seen from the table above, the p-value is not significant and is greater that Byrne's (2010) 0.05 cut-off. This confirms that there are no significant differences between the groups at the model level and we have achieved metric invariance. Differences at the path level within moderators will be explored at a later stage as part of the structural model moderation testing.

5.8 Multivariate Assumptions

There are a number of assumptions that must be met prior to using SEM. Therefore, the researcher investigated a number of these assumptions as discussed by a number of authors in this field (Byrne, 2010; Hair et al., 2010; Schumacker & Lomax, 2010).

5.8.1 Normality

An assumption used in for SEM parameters estimation is that observed factors are multivariate normally distributed, although, purely exogenous factors do not need to be normally distributed. Non-normality in this case may be as a result of using scaling variables (e.g. Likert Scale) rather than interval (Schumacker & Lomax, 2010).

Two most common statistical tests that are used to assess normality through the calculation of the significance in the difference from a normal distribution are the Shapiro-Wilks test and a modified version of the Kolmogorov-Smirnov test (Hair et al., 2010). The following hypotheses are formulated to investigate the normality of the data:

H_0: The distribution of the data is normal.
H_1: The distribution of the data is significantly different from a normal distribution.
The results of both tests are:

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BI	.215	497	.000	.885	497	.000
SI_IMG	.083	497	.000	.967	497	.000
SRE	.085	497	.000	.928	497	.000
SI_INF	.082	497	.000	.972	497	.000
ReInv	.131	497	.000	.955	497	.000
SL	.097	497	.000	.926	497	.000
EE	.092	497	.000	.970	497	.000
V	.043	497	.028	.990	497	.002

TandFC	.053	497	.002	.985	497	.000
PE	.064	497	.000	.971	497	.000

a. Lilliefors Significance Correction

Table 5.8 Kolmogorove-Smirmov Normality Testing

From the table above, it can be seen that, on both tests, all factors had a significant value below 0.05. Therefore, we reject the null hypotheses of having a normal distribution and conclude that the data is significantly different from a normal distribution. Therefore, there is a need to investigate for skewness and kurtosis which can be problematic in SEM (Byrne, 2010).

The composite constructs data were also checked for skewness and kurtosis:

BI	Mean	5.6699
	Skewness	-1.142
	Kurtosis	1.586
SI_IMG	Mean	4.5428
	Skewness	-0.569
	Kurtosis	0.388
SRE	Mean	5.5341
	Skewness	-1.232
	Kurtosis	3.307
SI_INF	Mean	4.2306
	Skewness	-0.447
	Kurtosis	-0.237
RelnV	Mean	4.427
	Skewness	-0.669
	Kurtosis	0.421

SL	Mean	5.8415
	Skewness	-1.063
	Kurtosis	2.576
EE	Mean	3.9977
	Skewness	0.013
	Kurtosis	-0.939
V	Mean	3.724
	Skewness	-0.251
	Kurtosis	-0.407
TandFC	Mean	4.3319
	Skewness	-0.291
	Kurtosis	-0.519
PE	Mean	5.0296
	Skewness	-0.468
	Kurtosis	-0.022

Table 5.9 Shapiro-Wilk Normality Test

As can be seen above, upon examination of the constructs, although the data was not perfectly normally distributed, skewness and kurtosis were within the acceptable range. Kline (2012) argues that the extremes are skewness > 3 and kurtosis > 10). A rule of thumb is that variables with kurtosis and skewness between -1 and +1 are reasonably close to normal. Aside from a few values, all of the values fall within this range, while these few that go beyond 1 are within Kline's (2012) suggested limits.

Moreover, just to be safe, the author ran an assessment of normality using SPSS AMOS software for both structural models. Results are reported in Appendix 10 and are discussed in the next chapter. However, they are mentioned here for support. Results of the assessment of normality for both structural models shown that all kurtosis values fall within the accepted range (-7 to 7), 0 being normally distributed (Byrne, 2010). However, there was an indication of multi-variate kurtosis which could occur even if kurtosis was within an acceptable range. This required further investigation to assess the impact on results. Such further investigation takes place later in the next chapter (6.4.1 Normality assessment revisited).

5.8.2 Multicollinearity

Another assumption of multiple regression statistics is the absence of multicollinearity in the data. The researcher tested the Variable Inflation Factor (VIF) for all the exogenous or independent variables. VIF is an indicator of the effect that another independent variable may have on the standard error of a regression coefficient (Hair et al., 2010).

Using SPSS, the following VIF output resulted when running a linear regression with BI as a dependent variable and the nine predictor variables: PE, EE, T, V, SL, SRE, ReInv, SIINF, and SIIMG.

Aside from SRE which had a VIF value of 3.230 which is considered acceptable, all variables had a VIF value that is less than 3, therefore, it is safe to say that there are no multicollinearity issues. Moreover, investigation of the correlation tables for both models presented in the chapter which can be found in Appendix 11 and Appendix 15 show no high correlations between independent variables. The presence of high correlations between independent variables can usually serve as a first indication of collinearity (Hair et al., 2010).

Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.574	.447		1.286	.199		
	SIIMG	.100	.042	.102	2.390	.017	.779	1.284

SRE	.593	.121	.332	4.883	.000	.310	3.230
SIINF	.015	.043	.015	.360	.719	.787	1.270
ReInv	.291	.078	.161	3.745	.000	.772	1.296
SL	-.205	.091	-.136	-2.245	.025	.387	2.582
EE	-.063	.030	-.085	-2.122	.034	.894	1.119
V	-.033	.063	-.029	-.521	.602	.447	2.237
T	.162	.048	.186	3.402	.001	.478	2.092
PE	.179	.040	.209	4.454	.000	.651	1.535

a. Dependent Variable: BI

Table 5.10 Multicollinearity Testing: Variable Inflation Factor (VIF)

5.8.3 Linearity and Homoscedasticity

One key assumption of multiple regression statistics is that residuals are normally distributed and that, across all levels of predictors, their variances are uniform (Kline, 2012). This is known as homoscedasticity. Moreover, another assumption in SEM is that variables are linearly related (Schumacker & Lomax, 2010). Linearity and homoscedasticity are aspects of multivariate normality (Kline, 2012). Hence, the researcher investigated whether these assumptions are met or not.

Using SPSS, a linear regression analysis was carried out using BI as a dependent variable and PE, EE, V, TandFC, SL, Reinv, SI_INF, SI_IMG, SRE, and SL as independent variables. The main purpose for running this was to look at the resulting histogram and scatter plot produced which is presented below.

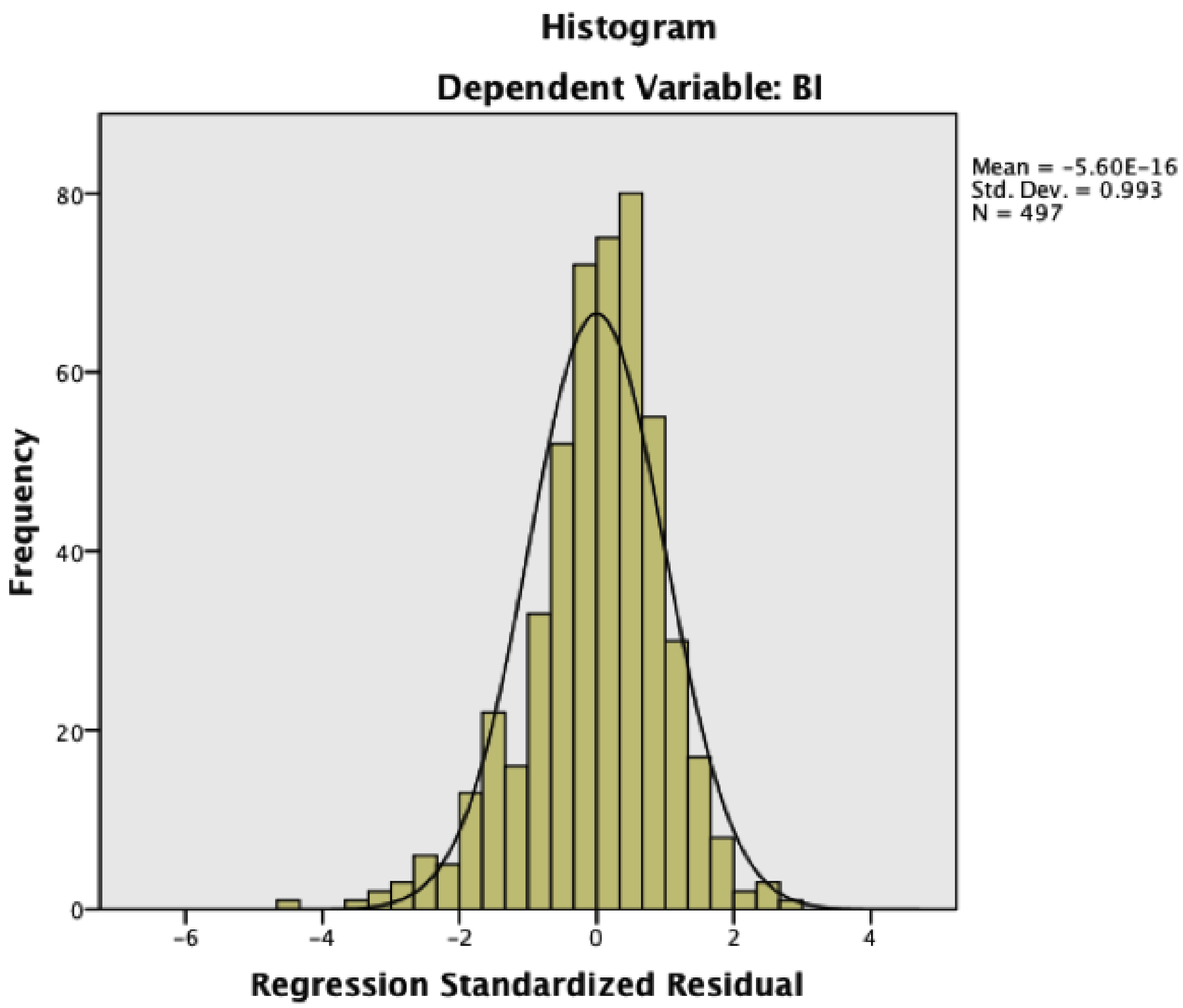

Figure 5.15 Linear Regression Histogram

From the histogram above, it can be seen that the regression standardised residual are almost normally distributed.

Furthermore, to assess whether heteroscedasticity is present in the data or not, using SPSS, two tests were applied and are reported below. These tests assess whether the estimated variance of residuals from a regression are dependent on independent variables values.

Breusch-Pagan test for Heteroscedasticity (CHI-SQUARE df=P)

66.308

Significance level of Chi-square df=P (**H_0**:homoscedasticity)

.0000

Koenker test for Heteroscedasticity (CHI-SQUARE df=P)

40.834

Significance level of Chi-square df=P (**H_0**:homoscedasticity)

.0000

The Chi-square values of both tests above show that null hypotheses of homoscedasticity should be rejected. Therefore, indicating heteroscedasticity of the data. This indicates that the standard errors estimates are not accurate.

Based on the above, it can be seen that heteroscedasticity is present.

The impact on the data and the analysis

Despite the fact that heteroscedasticity is present in the data, this is something to be expected especially since the data collected can be thought of as theoretically moderated. Meaning, data are collected from people from different groups. For instance, there are differences in age, experiences, education and so on. Since this is the case, we actually expect that there would be some heteroscedasticity in the relationships between the residuals and the values for each variable. Differences will also surface when different groups are looked at later on.

5.9 Summary

The aim in this chapter was to first examine the data following a number of data screening methods. Then, an exploratory factor analysis was used to understand the underlying structure from the data collected. Reliability and validity tests carried out at this stage confirmed the reliability and validity of the proposed model.

Then, the measurement model was developed and improved during the confirmatory factor analysis stage. This also allowed for further reliability and validity testing of the measurement model.

Common method bias or variance was found to influence a number of items and they were dropped from this study. Once that is done, reliability and validity tests were re-run. Results proved that the final measurement model was reliable and valid.

After deleting a single outlier case, the dataset was reduced to 496 useable cases (n).

Since the measurement model has proven to be reliable and valid, the next step was to develop the structural model, to investigate the various paths and test the hypotheses drawn earlier and summarised here:

#	Hypothesis
H1	Performance expectancy will have a significant and positive influence on behavioural intention
H2	Effort expectancy will have a significant and positive influence on behavioural intention
H3	Social influence will have a significant and positive influence on behavioural intention
H4a	Facilitating conditions will have a significant influence on behavioural intention
H4b	Facilitating conditions will have a significant influence on actual use
H5a	Results demonstrability will have a significant positive influence on behavioural

	intention
H5b	Results demonstrability will have a significant positive influence on performance expectancy
H6	Visibility will have a significant and positive influence on behavioural intention
H7	Trialability will have a significant positive influence on behavioural intention
H8	Reinvention will have a significant and positive influence on behavioural intention
H9	Students' requirements and expectations will have a significant and positive influence on behavioural intention
H10	Students' learning will have a significant and positive influence on behavioural intention
H11	behavioural intention will have a significant positive influence on actual use

Table 5.11 Summary of Hypotheses

6 Structural Models, Moderation, and Mediation

SEM is an analysis approach that uses models to explain relationships between multiple variables while at the same time allowing researchers to use latent factors to represent some concepts more accurately (Hair et al., 2010).

SEM is considered a confirmatory analysis technique that can be used to test and confirm theories (Hair et al., 2010). Therefore, the use of prior theory is important as the researcher has to specify the model before it can be run by the software package.

This study relied first on the literature to identify and develop a theoretical model (Chapter 2 and 3) to be considered as base model that is then analysed and tested using structural equation modeling (SEM). Then, in the previous chapter, data was collected and an EFA was run to identify underlying relationships between the various constructs. That structure was then converted into a measurement model, to assess the reliability and validity of the measures.

After concluding that the measurement model developed in the previous chapters and then tested in the previous chapter is valid, in this chapter, the measurement model was converted into hybrid model (measurement and structural model combined) to test the various hypotheses and confirm or explore any possible mediation and moderation effects.

Applications and steps taken by the researcher in this chapter are guided by the work of Byrne (2010), Hair et al. (2010), Kline (2012), and Kenny (2014) as key figures in this area. The researcher also benefitted a lot from the excellent videos, resources, lectures, and guidance provided by Gaskin (2012).

6.1 Hypothesized Model (Model 1)

Despite being able to impute variables within SPSS AMOS which could make analysis for such a complex model much easier, the author decided to continue with a hybrid model as it is more accurate to do so (error variances can be seen and controlled).

With the use of the measurement model that was developed in the previous chapter, the following hybrid (measurement and structural) model was created using maximum likelihood estimation method which is appropriate for the sample size (n:496) of this study (Hox & Bechger, 2007; Kline, 2012):

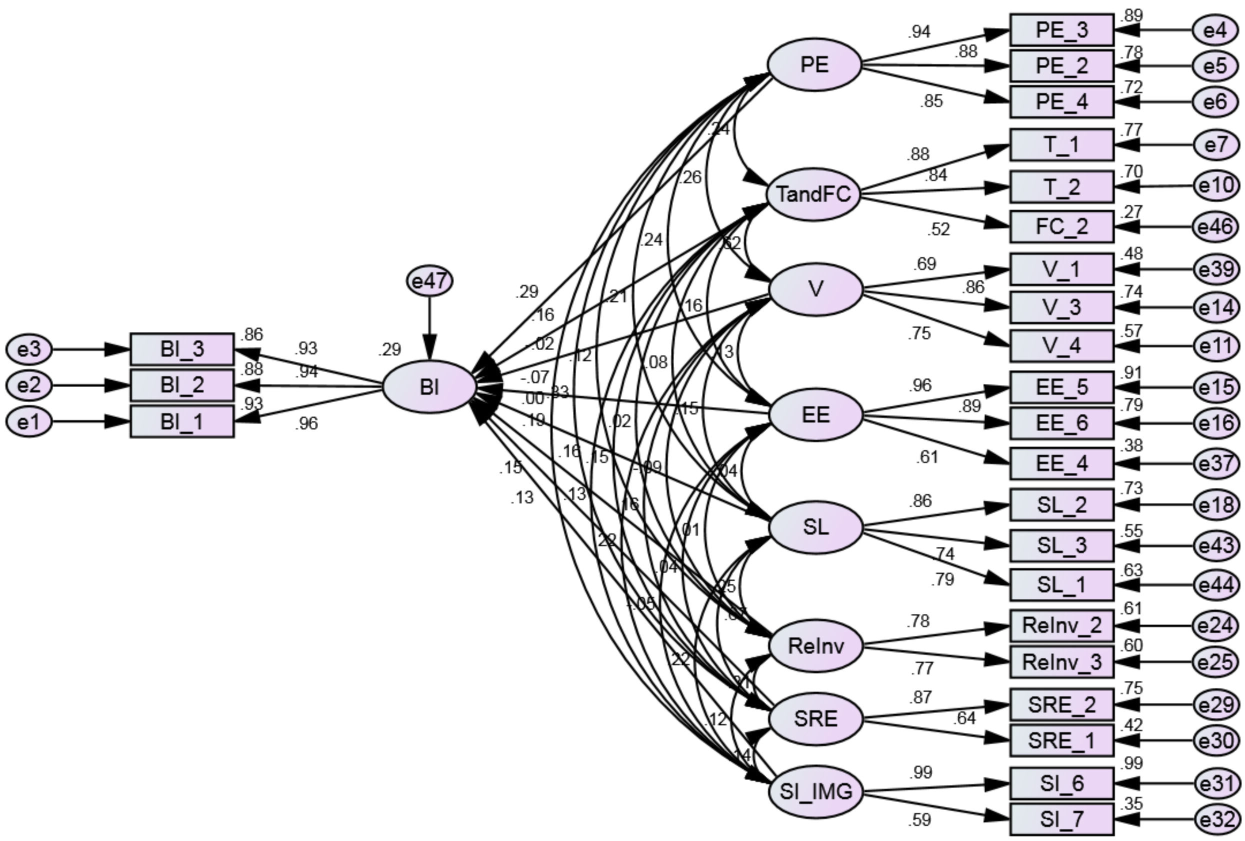

Figure 6.1 Hybrid Structural Model (Original Model 1)

As a result of a Heywood case, the error variance e31 for item SI_6 had to be fixed to be non-negative (Kenny, 2014), as otherwise, loadings would be higher than one which is illogical. The value was fixed to 0.02 to have minimum impact, as the researcher found that a high fixed value would influence loadings and the construct's relationship to the dependent construct (BI). Also, having a high error variance sometimes can cause regression estimates to become > 1. Such unexpected estimates may surface as a result of a sample issue (e.g. differences in responding), outliers, or as a result of using less than four items per factor (Kline, 2012; Schumacker & Lomax, 2010).

The resulting model had an R^2=.29 for the dependent variable (BI), Chi-square value of 441.444, and 217 Degrees of freedom (DoF). Therefore, the model explained 29% of the variance in behavioural intention (BI).

As a first step of testing the proposed model, we examined the goodness-of-fit (GOF) indices.

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	2.034	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.932	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.906	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.967	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.760	Recommended to be above 0.8
PCLOSE:	.876	Recommended to be above 0.05
RMSEA:	.046	Recommended to be less than 0.1

		Better if less than 0.05

Table 6.1 Hybrid Structural Model (Original Model 1) GOF

Based on the acceptable model fit, the researcher evaluated the paths between the latent variables in the model. The following are the standardised regression weights for the relationships between the independent variables (IVs) and the dependent variable (DV):

Standardised Regression Weights

	Estimate	S.E.	C.R.	P
BI <--- PE	0.291	0.042	6.068	***
BI <--- TandFC	0.157	0.054	2.565	0.01
BI <--- V	-0.016	0.062	-0.255	0.799
BI <--- EE	-0.072	0.033	-1.663	0.096
BI <--- SL	0.001	0.096	0.008	0.994
BI <--- ReInv	0.187	0.077	3.565	***
BI <--- SRE	0.147	0.109	1.973	0.048
BI <--- SI_IMG	0.135	0.04	3.143	0.002

Table 6.2 Hybrid Structural Model (Original Model 1) Standardised Regression Weights

Standardised estimates with critical ratios (C.R.) > 1.96 are statistically significant (Byrne, 2010) and the p-values also reflect this.

From the above, it can be seen that the paths from the following independent variables to the dependent variable are significant at the 0.05 level and their hypotheses are supported: PE, TandFC, ReInv, SRE, and SI_IMG. The strongest of the paths is PE —> BI with a standardised estimate of 0.291 ($p < 0.001$). The rest of the estimates, especially those much below .2, although significant, are not considered meaningful for discussion (Hox & Bechger, 2007).

6.1.1 Correlations

In multiple regression (but also in SEM which is built on it), there should be no high correlations between predictor variables as otherwise, they may be measuring the same thing (Brace et al., 2012).

Upon investigation of correlations between predictor variables (Appendix 11), some high correlations were found between: TandFC <—> V and SL <—> SRE. Upon further investigation, items forming all of these constructs show no sign of over-lapping when investigating the modification indices (MIs) output. Possible overlaps or cross-loadings would show in the MI output of AMOS if there were such issues (Byrne, 2010). Therefore, we conclude that it is likely that these constructs are related but they are not measuring the same thing. Covariances for this model are also reported in Appendix 11. Reporting correlations, covariances, and residuals is considered a good practice for studies using SEM (Schumacker & Lomax, 2010).

6.1.2 Direct Effects

SPSS AMOS reports total effects of one variable on another, consisting of direct and indirect effects. Standardised and unstandardised direct effects are reported in Appendix 12. Indirect effects were not reported for this model as it does not have any mediating variables and all values would be reported as 0. Therefore, the only applicable output is the direct effects.

Investigating the standardised direct effect shows PE to have the most influence on BI followed by ReInv.

6.1.3 Moderation Testing

Now that the structural model is developed, the researcher investigated a number of categorical moderation factors that may cause differences on the path level across groups. The categorical factors that will be tested as moderations are: **Gender, Age, Experience, Education, Yearly Teaching Hours, Mandatory or Voluntariness of Adoption, and Country**. Reponses related to these moderating variables were captured as part of the online questionnaire used by this study.

Moderation testing can be done using multi group SEM (Hair et al., 2010) where the moderator or grouping factor is defined and the different group values are assigned. Then, tests of groups differences are done to investigate which differences between groups are indeed significant.

Using the Stats Tool Package (Gaskin, 2012) and after enabling critical ratio of differences in AMOS's output, the Group Differences tab of the Stats Tools Package was used to calculate the significance of the differences between model paths of the different groups. The tool calculates a z-score based on regression weights and critical ratios for differences outputs from AMOS for the different groups in question.

Under each moderator, the model-fit parameters will be reported, showing how good the model is for each moderator. All moderators used and reported below are categorical moderators. Regression weights are reported in the estimate column. Moreover, the p-value is reported for each effect.

For some moderated models, some error variances were negative and they had to be fixed to a low value of 0.02. This is to ensure the value does not influence the model or loadings of the items, as explained above. All moderated models are presented in Appendix 13 (Moderated Models). All moderated models shown very well goodness-of-fit parameters.

Furthermore, calculated z-scores for group differences for each moderation group are presented in Appendix 14 (Moderation Groups Z-Scores).

6.1.3.1 Significant differences between group

Across all of the groups, only two significant differences between moderation groups were found worthy of reporting.

<u>Gender:</u>

ReInv —> BI

The effect is not significant and weaker for Females. On the other hand, it is significant and much stronger for Males. This may indicate that for Males, ReInv has a stronger effect and that being able to change or tweak the innovation before adopting and using it is important.

<u>Age:</u>

TandFC —> BI

The effect is not significant and much weaker for those over 50 years old. On the other hand, it is significant and much stronger for the younger member of staff in the 30-50 Years old group. This suggests that TandFC becomes less influential as age increases. Therefore, having no impact on BI for older people.

6.1.3.2 Noticeable differences

Although the z-scores calculated for the following relationships did not indicate a significance difference, there were some noticeable differences between groups that are worth exploring.

<u>Gender:</u>

PE —> BI

The effect is significant for both groups. However, the effect is stronger for males. This suggests that for male members of staff, PE is more important.

<u>Age:</u>

PE —> BI

The effect is significant for both groups. However, the effect is much stronger (almost twice as strong) for those over 50 years old. This suggests that for older member of staff, PE is more important.

ReInv —> BI

The effect is significant for both groups. However, the effect is stronger for those over 50 years old. This suggests that for older member of staff, ReInv is more important.

SI_IMG —> BI

The effect is not significant for those over 50 years old. On the other hand, it is significant for the younger member of staff in the 30-50 Years old group. This suggests that SI_IMG becomes less influential as age increases. Therefore, having no impact on BI for older people.

<u>Experience:</u>

PE —> BI

The effect is significant for both groups. However, the effect is stronger for those with less experience (5-9 Years of experience) than it is for more experienced members of staff. This suggests that for members of staff with less experience, PE is more important.

ReInv —> BI

The effect is not significant for those with less experience (5-9 Years). On the other hand, it is significant and slightly stronger for the more experienced members of staff (Over 9 Years). This suggests that ReInv is more important for those with more experience.

SI_IMG —> BI

The effect is not significant for those with less experience (5-9 Years). On the other hand, it is significant and slightly stronger for the more experienced members of staff (Over 9 Years). This suggests that SI_IMG becomes more influential as work experience increases.

Education:

TandFC —> BI

The effect is not significant for those with Doctorate education. On the other hand, it is significant and slightly stronger for those with Masters education. This suggests that TandFC may be less influential for those with Doctorate education.

ReInv —> BI

The effect is not significant for those with Masters education. On the other hand, it is significant for those with Doctorate education. This suggests that ReInv may be more influential for those with Doctorate education.

SI_IMG —> BI

The effect is not significant for those with Masters education. On the other hand, it is significant for those with Doctorate education. This suggests that SI_IMG may be more influential for those with Doctorate education.

Teaching Hours:

PE —> BI

The effect is not significant for those teaching more hours per year (501-1000). On the other hand, it is significant for those teaching less hours per year (51-500). This suggests that PE is more influential for those teaching less.

TandFC —> BI

The effect is not significant for those teaching more hours per year (501-1000). On the other hand, it is significant and stronger for those teaching less hours per year (51-500). This suggests that TandFC is more influential for those teaching less.

ReInv —> BI

The effect is not significant for those teaching more hours per year (501-1000). On the other hand, it is significant and stronger for those teaching less hours per year (51-500). This suggests that ReInv is more influential for those teaching less.

SI_IMG —> BI

The effect is not significant for those teaching more hours per year (501-1000). On the other hand, it is significant and slightly stronger for those teaching less hours per year (51-500). This suggests that SI_IMG is more influential for those teaching less.

<u>Voluntary/Mandatory Adoption:</u>

PE —> BI

The effect is significant for both groups. However, the effect is slightly stronger for those in the mandatory adoption group. This suggests that PE maybe more influential for mandatory adopters.

SI_IMG —> BI

The effect is not significant for those in the mandatory adoption group. On the other hand, it is significant for those in the voluntary group. This suggests that SI_IMG is more influential for voluntary adopters.

<u>Country:</u>

TandFC —> BI

The effect is not significant for those from England or Wales. On the other hand, it is significant and stronger (more than twice as strong as the highest) for those from Scotland. This suggests that TandFC is more influential for those from Scotland.

ReInv —> BI

The effect is not significant for those from Scotland and Wales. On the other hand, it is significant and stronger for those from England. This suggests that ReInv is more influential for those from England.

SI_IMG —> BI

The effect is not significant for those from Scotland. On the other hand, it is significant and slightly stronger for those from England or Wales. This suggests that SI_IMG is more influential for those from England or Wales.

6.2 Post-Hoc Analysis & Alternative Model (Model 2)

In the previous section/chapter the hybrid model was created with the theory in mind, as the researcher had a theoretical model which was discussed before. However, in this section, the researcher followed what is known as a post-hoc analysis. Post-hoc analysis is usually undergone if the model was inadequate to fit the previously hypothesised model and the data, in which case, the process becomes more exploratory (Byrne, 2010).

Furthermore, it is not unusual for researchers to explore and find new relationships or findings and this is most certainly the case when using approaches such as SEM; as the model can be developed in an exploratory way allowing the researcher to investigate and try to reach a model that would explain the data better.

Similar to what have been while improving the measurement model in the CFA stage, **Modification indices** within SPSS AMOS (and other SEM software) provides useful information on what constructs maybe related to each other. In particular, if the model-fit was not good or the researcher was trying to reach a better model, relationships suggested by the modification indices maybe added (Hair et al., 2010; Hox & Bechger, 2007).

High modification indices within SPSS AMOS shows that variables are highly related and creating regression paths within the model would mean that one of the variables would predict or explain the variance in the other variable very well.

Taking into consideration Byrne’s (2010) warning of the need for researchers to be aware of the dangers associated with post-hoc analysis, the researcher here does not plan to over improve an already good model. Instead, the researcher plans to follow the exploratory nature of the post-hoc analysis to investigate possible alternative models that may explain the data too or help uncover new findings. Such exploration and model respecification will be limited to those tested new relationships that either have prior theoretical support or are substantively meaningful (Byrne, 2010; Hair et al., 2010).

The researcher although started this research following a deductive reasoning approach, to test the originally proposed model, in this chapter, the researcher changed into an exploratory mode (Byrne, 2010), investigating further relationships and relevant evidences that may help uncover some interesting findings from the data.

The researcher believes that this is the right decision considering the proposed model was not tested before and other relationships may surface. Additionally, the use of SEM software allows for easy development and testing of various models and relationships. Thus, the objective here is not necessarily to reach a better model, but more importantly, to take into consideration and test alternative relationships that may help in explaining and understanding the adoption of learning innovations better.

6.2.1 Starting with possible alternatives in mind

Building on the results of the previous model, EE had an insignificant path to BI. Similar studies found that this is the case (Jong & Wang, 2009; Park, 2009; Selim, 2003; Sumak et al., 2010) while others suggested that EE (or PEOU) may influence PE (PU) (Lin & Lu, 2000; Martins & Kellermanns, 2004; Saadé et al., 2007). Therefore, PE became an endogenous or dependent variable in this post-hoc model to investigate whether it can be predicted by EE and whether it may act as a mediator as well (EE - PE - BI).

Moreover, by examining estimates and modification indices, it was found that V and TandFC both had a strong relationship evidenced by their higher correlation of .622 in the previous model. From a logical perspective, such relationship can be accepted. When the visibility of a learning innovation increases, it is likely that the perception of the facilitating conditions being supportive increases. There is also another alternative explanation. When facilitating conditions are in place to support the implementation of a certain learning innovation, it is likely that more would implement the learning innovation. Hence, the learning innovation becoming more visible.

After a number of tests and by investigating the regression weights estimates and the modification indices, the researcher was able to reach the following model that fits the data very well (n:496):

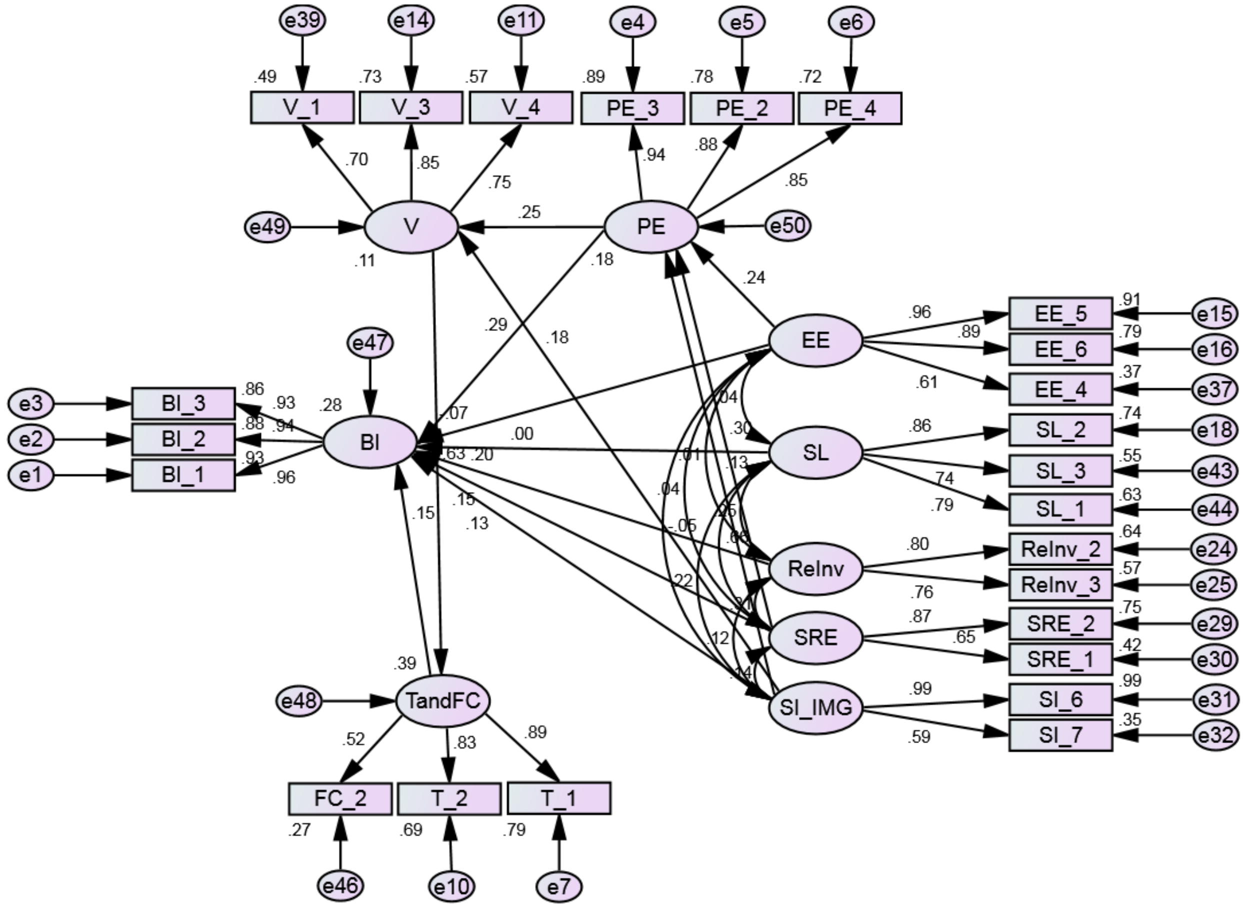

Figure 6.2 Initial Post-Hoc Mode

The resulting model had an R^2=.28 for the dependent variable (BI), Chi-square value of 464.745, and 230 Degrees of freedom (DoF). Therefore, the model explained 28% of the variance in behavioural intention (BI). However, the model also shown interesting relationships explored below.

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	2.021	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.929	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.907	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.965	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.804	Recommended to be above 0.8
PCLOSE:	.899	Recommended to be above 0.05
RMSEA:	.045	Recommended to be less than 0.1 Better if less than 0.05

Table 6.3 Initial Post-Hoc Model GOF

Based on the acceptable model fit, we evaluated the paths between the latent variables in the model. The following are the standardised regression weights for the relationships between the independent variables (IVs) and the dependent variable (DV):

Standardised Regression Weights

			Estimate	S.E.	C.R.	P
PE	<---	EE	0.238	0.04	5.254	***
PE	<---	SRE	0.296	0.086	5.787	***
PE	<---	SI_IMG	0.13	0.047	2.946	0.003
V	<---	PE	0.248	0.044	5.004	***
V	<---	SI_IMG	0.181	0.045	3.791	***
TandFC	<---	V	0.628	0.057	12.198	***
BI	<---	EE	-0.07	0.033	-1.646	0.1
BI	<---	SL	-0.003	0.095	-0.044	0.965
BI	<---	ReInv	0.195	0.077	3.813	***
BI	<---	SRE	0.148	0.107	2.012	0.044
BI	<---	SI_IMG	0.132	0.039	3.14	0.002
BI	<---	TandFC	0.146	0.039	3.331	***
BI	<---	PE	0.294	0.041	6.213	***

Table 6.4 Initial Post-Hoc Mode Standardised Regression Weights

Standardised estimates with critical ratios (C.R.) > 1.96 are statistically significant (Byrne, 2010) and the p-values reflect this.

From the above, it can be seen that all paths except for those from EE & SL are significant at the 0.05 level. V —> TandFC shows a very strong and significant relationship, the strongest of all the paths. EE had a significant effect on PE while all paths from SL were not significant. Therefore, SL was dropped. This resulted in the following slightly improved model:

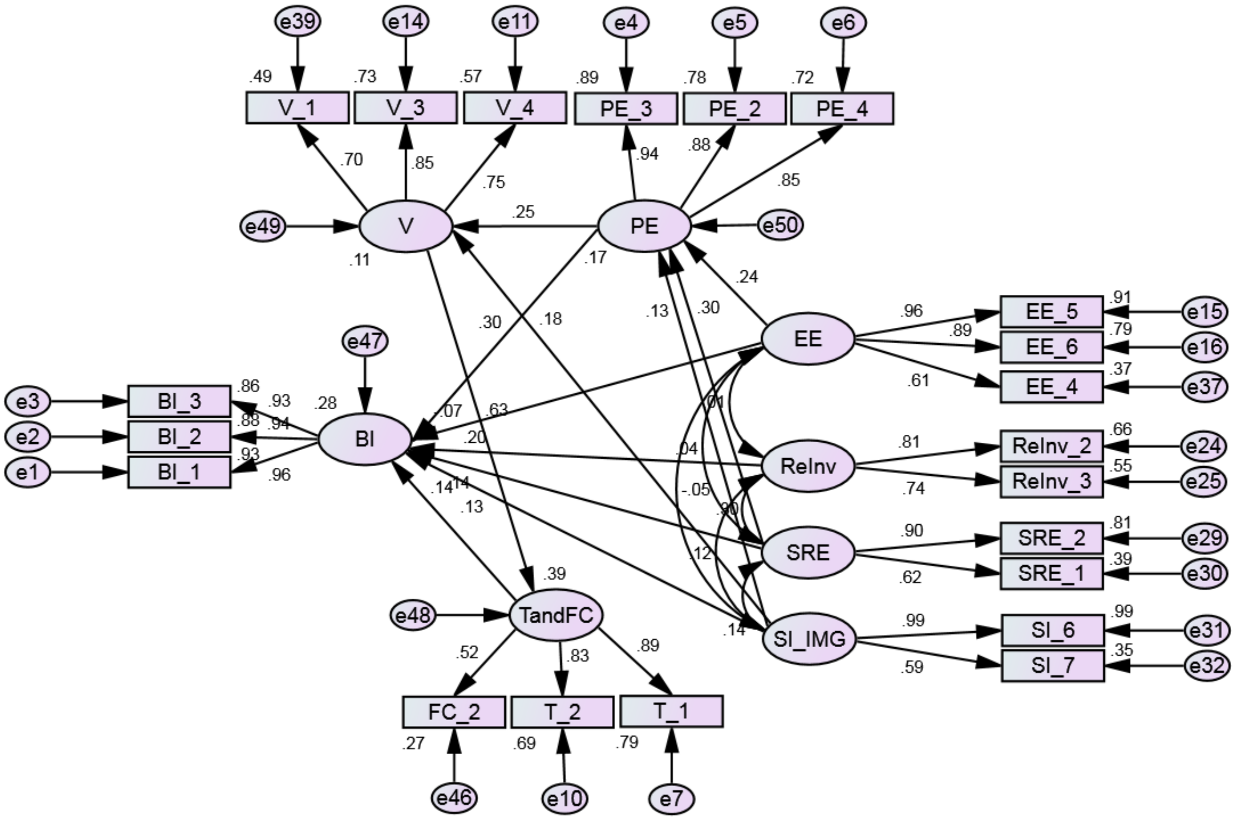

Figure 6.3 Post-Hoc Model without SL

The model fit summary was:

Model-Fit Parameters	Obtained Values	Recommended Values (Hair et al., 2010)
CMIND/DF:	1.802	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.945	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.927	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.977	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.

PCFI:	.800	Recommended to be above 0.8
PCLOSE:	.989	Recommended to be above 0.05
RMSEA:	.040	Recommended to be less than 0.1 Better if less than 0.05

Table 6.5 Post-Hoc Model without SL GoF

6.2.2 Outliers

Despite the fact that the model fits the data very well, the researcher looked at multivariate outliers within AMOS. AMOS can report the Mahalanobis d-squared values for observations. The researcher wanted to investigate whether removing some outliers that are far from the rest of the observations would improve the model and the explained variance for the dependent variable (BI). Using AMOS's output for outliers, observations with a very low p1 value and too large Mahalanobis d-squared values that are far from the rest of observations are candidates for removal.

Based on the Mahalanobis d-squared values for observations presented by SPSS AMOS, a number of cases were removed from the study. This resulted in the slightly improved model below.

6.2.3 Final Post-Hoc Model

After removing a number of outliers, the final post-hoc model (n:464) is:

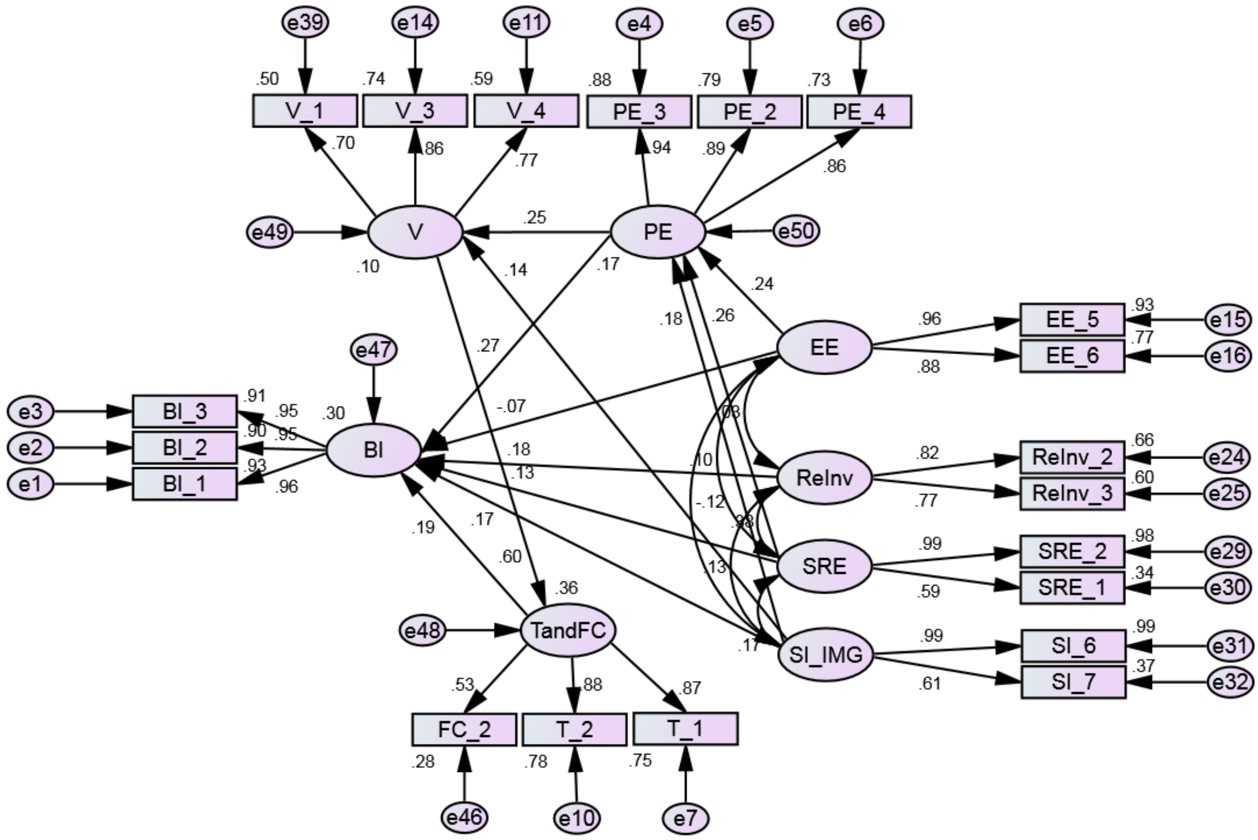

Figure 6.4 Final Post-Hoc Model

As can be seen, removing a number of cases that are considered outliers improved the variance explained for the behavioural intention dependent variable from being 28% to 30%.

The resulting model had an R^2=.30 for the dependent variable (BI), Chi-square value of 223.367, and 153 Degrees of freedom (DoF). Therefore, the model explained 30% of the variance in behavioural intention (BI). However, the model also shown interesting relationships explored below.

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	1.460	Below 5. The less, the better
P:	.000	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.953	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.
AGFI:	.936	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.988	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.795	Recommended to be above 0.8
PCLOSE:	1.000	Recommended to be above 0.05
RMSEA:	.032	Recommended to be less than 0.1 Better if less than 0.05

Table 6.6 Final Post-Hoc Model GOF

The following are the standardised regression weights for the relationships between the independent variables (IVs) and the dependent variable (DV):

Standardised Regression Weights

			Estimate	S.E.	C.R.	P
PE	<---	EE	0.243	0.044	4.892	***
PE	<---	SRE	0.256	0.097	4.57	***
PE	<---	SI_IMG	0.178	0.049	3.873	***
V	<---	PE	0.253	0.046	4.9	***
V	<---	SI_IMG	0.142	0.048	2.848	0.004
TandFC	<---	V	0.598	0.058	11.127	***
BI	<---	EE	-0.066	0.034	-1.501	0.133
BI	<---	RelInv	0.182	0.074	3.479	***
BI	<---	SRE	0.13	0.078	2.519	0.012
BI	<---	SI_IMG	0.165	0.04	3.858	***
BI	<---	TandFC	0.19	0.04	4.298	***
BI	<---	PE	0.273	0.041	5.733	***

Table 6.7 Final Post-Hoc Model Standardised Regression Weights

Standardised estimates with critical ratios (C.R.) > 1.96 are statistically significant (Byrne, 2010) and the p-values reflect this.

From the above, it can be seen that all paths except for EE —> BI are significant at the p-value < 0.05 level. V —> TandFC shows a very strong and significant relationship, the strongest of all the paths. Also, EE had a significant effect on PE.

6.2.4 Correlations

As explained earlier, there should be no high correlations between predictor variables; otherwise, they may be measuring the same thing (Brace et al., 2012).

Upon investigation of correlations between predictor variables (Appendix 15), no high correlations were found. Covariances for this model are also reported in Appendix 15. Reporting correlations, covariances, and residuals is considered a good practice for studies using SEM (Schumacker & Lomax, 2010).

6.2.5 Total Effects (Direct and Indirect)

Standardised and unstandardised total effects as well as direct and indirect effects for this model are reported in Appendix 16.

Investigating the standardised total effects shows PE to have the highest influence on BI followed by SI_IMG and SRE. The highest two standardised indirect (mediated) effects found were those from PE —> TandFC and V —> BI.

6.2.6 Combining Variables

To gain better insight into conditions or cases where the relationships or the model may perform differently, the researcher will test moderation and mediation effects in the model. However, prior to doing that, and as a result of the model being a lot more complex than the original theoretical model, and to make it easier to run the various tests and for the readers to follow, the researcher imputed the variables from the hybrid model. This resulted in a much simpler SEM model. Below are the model and the model-fit parameters reported prior to running any tests.

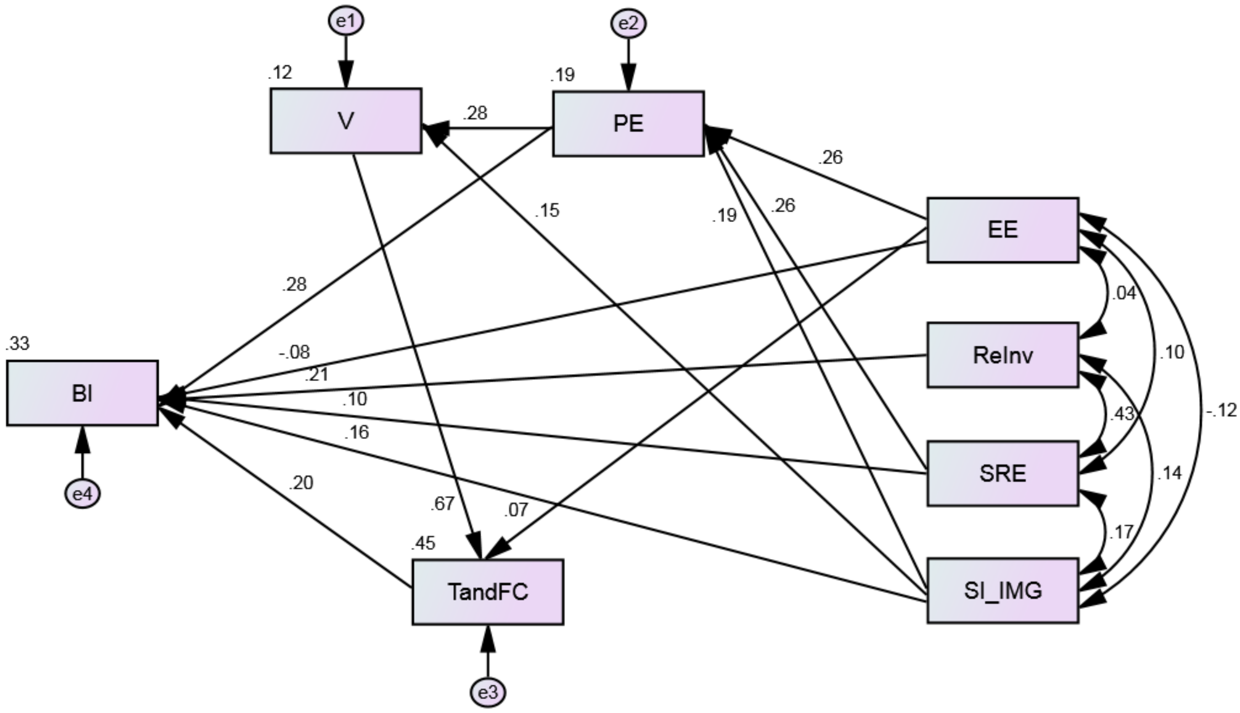

Figure 6.5 Post-Hoc Model Simplified

The model had an R^2=.33 for the dependent variable (BI), Chi-square value of 14.103, and 9 Degrees of freedom (DoF). Therefore, the model explained 33% of the variance in behavioural intention (BI).

The model fit summary was:

Model-Fit Parameters	**Obtained Values**	**Recommended Values** (Hair et al., 2010)
CMIND/DF:	1.567	Below 5. The less, the better
P:	.119	A larger sample causes P to be significant. Therefore, it won't be taken into account. If the sample was small, a significant value here indicates a bad model fit.
GFI:	.992	Between 0-1. Higher values indicate good model fit. A value of 1 indicates perfect fit.

AGFI:	.970	Between 0-1. Higher values indicate good model fit. Recommended to be above .80
CFI:	.993	Between 0-1. Higher values indicate good model fit. Values close to 1 indicate very good fit.
PCFI:	.319	Recommended to be above 0.8
PCLOSE:	7.35	Recommended to be above 0.05
RMSEA:	.035	Recommended to be less than 0.1 Better if less than 0.05

Table 6.8 Post-Hoc Model Simplified GOF

As can be seen from the model-fit parameters, the model shows an insignificant p-value, indicating good model fit. However, the researcher will not rely on p-value as a robust measure of goodness of fit as it becomes inaccurate if the sample size is large as explained before. P-value may have moved from the .000 reported before due to the low degrees of freedom as a result of imputing many variables.

6.2.7 Moderation Testing

The researcher looked at a number of categorical moderation factors that may cause differences on the path level across groups. The categorical factors that will be tested as moderations are: Gender, Age, Experience, Education, Yearly Teaching Hours, Mandatory or Voluntariness of Adoption, and Country. These were captured as part of the online questionnaire used by this study.

Under each moderator, the model-fit parameters will be reported, showing how good the model is for each moderator. All moderators used and reported below are categorical moderators. Regression weights are reported in the estimate column. Moreover, the p-value is reported for each effect.

For some moderated models, some error variances were negative and they had to be fixed to a low value of 0.02. This is to ensure the value does not influence the model or loadings of the items. All moderated models are presented in Appendix 17 (Post-Hoc Moderated Models). All moderated models shown very well goodness of fit parameters.

Furthermore, calculated z-scores for group differences for each moderation group are presented in Appendix 18 (Post-Hoc Model Moderated Groups Z-Scores).

6.2.7.1 Significant differences between group

Across all of the groups, a number of significant differences between moderation groups were found worthy of reporting.

Age:

SRE —> PE

The effect is significant for both groups. However, the effect is much stronger for younger staff (30-50 years old). This suggests that for this group, the influence of SRE on PE is stronger.

SI_IMG —> V

The effect is not significant for those over 50 years old. On the other hand, it is significant and stronger for the younger staff (30-50 years old). This suggests that for this group, the influence of SI_IMG on V is stronger.

V —> TandFC

The effect is significant for both groups. However, the effect is stronger for younger staff (30-50 years old). This suggests that for this group, the influence of V on TandFC is stronger.

<u>Experience:</u>

SI_IMG —> PE

The effect is not significant for those less experienced (less than 5 years). On the other hand, the effect is significant for those with more experience (5-9 years and more than 9 years). However, for those with more experience, the effect is much stronger for those with 5-9 years of experience. Despite being significant, the effect is weaker for those with over 9 years of experience. This suggests that the influence of SI_IMG on PE is much stronger for those with 5-9 years of experience.

EE —> PE

The effect is significant across all groups. However, the effect is much stronger for those with less than 9 years of experience (Less than 5 years and 5-9 Years). On the other hand, for those with over 9 years of experience, the effect is weaker. This suggests that the influence of EE on PE is much stronger for those with less experience and that as work experience increases, the influence decreases.

SRE —> BI

The effect is not significant for those with less experience (less than 5 years). On the other hand, it is significant and stronger for more experienced staff (Over 9 Years). This suggests that the influence of SRE on BI is stronger for those with much more experience (more than 9 years).

<u>Teaching Hours:</u>

SI_IMG —> V

The effect is not significant for those with fewer teaching hours (51-500 hrs/y). On the other hand, the effect is significant and much stronger for those with more teaching hours (501-1000 hrs/y). This suggests that the influence of SI_IMG on V is much stronger for those teaching 501-1000 hours/year.

SRE —> BI

The effect is not significant for those with fewer teaching hours (51-500 hrs/y). On the other hand, the effect is significant and much stronger for those with more teaching hours (501-1000 hrs/y). This suggests that the influence of SRE on BI is much stronger for those teaching 501-1000 hours/year.

TandFC —> BI

The effect is not significant for those with more teaching hours (501-1000 hrs/y). On the other hand, the effect is significant and much stronger for those with fewer teaching hours (51-500 hrs/y). This suggests that the influence of TandFC on BI is much stronger for those teaching 501-1000 hours/year.

<u>Voluntary of Adoption:</u>

ReInv —> BI

The effect is not significant for those in the mandatory adoption group. On the other hand, the effect is significant and much stronger for those in the voluntary adoption group. This suggests that the influence of ReInv on BI is much stronger for voluntary adopters.

TandFC —> BI

The effect is significant for both groups. However, the effect is stronger for those in the mandatory group. This suggests that for this group, the influence of TandFC on BI is stronger.

Country:

EE —> PE

The effect is significant across all groups. However, the effect is much stronger for those from England. This suggests that for this group, the influence of EE on PE is much stronger.

SI_IMG —> V

The effect is not significant for those from Scotland or Wales. On the other hand, the effect is significant and much stronger for those from England. This suggests that for this group, the influence of SI_IMG on V is much stronger.

TandFC —> BI

The effect is not significant for those from Wales. On the other hand, the effect is significant for those from England or Scotland. However, the effect is much stronger for those from Scotland. This suggests that for this group, the influence of TandFC on BI is much stronger.

ReInv —> BI

The effect is not significant for those from Wales. On the other hand, the effect is significant for those from England or Scotland. However, the effect is much stronger for those from England. This suggests that for this group, the influence of ReInv on BI is much stronger.

PE —> V

The effect is significant across all groups. However, the effect is much stronger for those from Wales. This suggests that for this group, the influence of PE on V is much stronger.

6.2.7.2 Noticeable differences

Although the z-scores calculated for the following relationships did not indicate a significance difference, there were some noticeable differences between groups that are worth exploring.

Gender:

SI_IMG —> V

The effect is not significant for males. On the other hand, the effect is significant and stronger for females. This suggests that the influence of SI_IMG on V is stronger for females.

ReInv —> BI

The effect is significant for both groups. However, the effect is stronger for males. This suggests that for this group, the influence of ReInv on BI is stronger.

Age:

EE —> BI

The effect is not significant for those 30-50 years old. On the other hand, the effect is significant and stronger for those over 50 years old. This suggests that for this group, the influence of EE on BI is stronger.

SRE —> BI

The effect is not significant for those 30-50 years old. On the other hand, the effect is significant and stronger for those over 50 years old. This suggests that for this group, the influence of SRE on BI is stronger.

SI_IMG —> BI

The effect is not significant for those over 50 years old. On the other hand, the effect is significant for those 30-50 years old. This suggests that for this group, the influence of SRE on BI is stronger.

Experience:

SRE —> PE

The effect is significant across all groups. However, the effect is stronger for those with less experience (less than 5 years). This suggests that for this group, the influence of SRE on PE is stronger.

PE —> V

The effect is not significant for those who have less than 5 years of experience. On the other hand, the effect is significant and slightly stronger for those with more experience (more than 5 years). This suggests that for these groups, the influence of PE on V is stronger.

SI_IMG —> V

The effect is not significant for those who have 5-9 years of experience. On the other hand, the effect is significant for those with less experience (less than 5 years) and those with much more experience (over 9 years). However, the effect is stronger for those with less experience (less than 5 years). This suggests that for this group, the influence of SI_IMG on V is stronger.

EE —> TandFC

The effect is not significant for those who have more than 5 years of experience. On the other hand, the effect is significant and stronger for those with less experience (less than 5 years). This suggests that for this group, the influence of EE on TandFC is stronger.

TandFC—> BI

The effect is not significant for those who have 5-9 years of experience. On the other hand, the effect is significant and stronger for those with less experience (less than 5 years) and those with much more experience (over 9 years). This suggests that for these groups, the influence of TandFC on BI is stronger.

SRE—> BI

The effect is not significant for those who have less than 9 years of experience. On the other hand, the effect is significant and stronger for those with more experience (over 9 years). This suggests that for this group, the influence of SRE on BI is stronger.

SI_IMG—> BI

The effect is not significant for those who have less than 9 years of experience. On the other hand, the effect is significant and stronger for those with more experience (over 9 years). This suggests that for this group, the influence of SI_IMG on BI is stronger.

Education:

SI_IMG —> PE

The effect is not significant for those with an MSc degree. On the other hand, the effect is significant and stronger for those with a Doctorate degree. This suggests that for this group, the influence of SI_IMG on PE is stronger.

SI_IMG —> V

The effect is not significant for those with an MSc degree. On the other hand, the effect is significant and slightly stronger for those with a Doctorate degree. This suggests that for this group, the influence of SI_IMG on V is stronger.

SI_IMG —> BI

The effect is not significant for those with an MSc degree. On the other hand, the effect is significant and slightly stronger for those with a Doctorate degree. This suggests that for this group, the influence of SI_IMG on BI is stronger.

<u>Teaching Hours:</u>

SRE —> PE

The effect is not significant for those with more teaching hours (501-1000 hrs/y). On the other hand, the effect is significant and stronger for those with fewer teaching hours (51-500 hrs/y). This suggests that for this group, the influence of SRE on PE is stronger.

PE —> V

The effect is not significant for those with more teaching hours (501-1000 hrs/y). On the other hand, the effect is significant and stronger for those with fewer teaching hours (51-500 hrs/y). This suggests that for this group, the influence of PE on V is stronger.

ReInv —> BI

The effect is not significant for those with more teaching hours (501-1000 hrs/y). On the other hand, the effect is significant and much stronger for those with fewer teaching hours (51-500 hrs/y). This suggests that for this group, the influence of ReInv on BI is stronger.

SI_IMG —> BI

The effect is not significant for those with more teaching hours (501-1000 hrs/y). On the other hand, the effect is significant and slightly stronger for those with fewer teaching hours (51-500 hrs/y). This suggests that for this group, the influence of ReInv on BI is stronger.

Voluntary of Adoption:

SI_IMG —> V

The effect is not significant for those in the mandatory group. On the other hand, the effect is significant and slightly stronger for those in the voluntary group. This suggests that for this group, the influence of SI_IMG on V is stronger.

V —> TandFC

The effect is significant for both groups. However, the effect is stronger for those in the mandatory group. This suggests that for this group, the influence of V on TandFC is stronger.

6.2.8 Mediation

As there are a number of dependent variables (DVs) or endogenous variables in this model, the researcher investigated whether there are any meditation effects in the model that might help explain some of the relationships more accurately.

The researcher used two different methods to investigate mediation effects. The first one is similar to the Baron and Kenny (1986) approach where four steps are followed to investigate whether there is a possible mediation effect taking place or not. The second approach is where mediation testing is done using AMOS's bootstrapping.

6.2.8.1 Simple Mediation Testing (Baron and Kenny approach)

Following the Baron and Kenny (1986) approach, there are four steps that need to be taken to establish the possibility of a mediation:

1. Show that the independent variable (IV) is correlated with the (DV) outcome variable. This step confirms whether there is an effect that may possibly be mediated.
2. Show that the independent variable (IV) is correlated with the mediator.
3. Show that the mediator affects the dependent variable (DV).
4. Investigate and establish that the mediator completely mediated the effect between the independent variable (IV) to the dependent variable (DV).

If all of these four steps are met, this indicates that the data are consistent with the hypothesis that the mediator fully mediates the relationship between the IV to the DV. If, however, only the first three steps are met, this indicates that the relationship is partially mediated.

Mediator: PE

The research investigated whether PE is mediating any paths. From the tables in Appendix 19, it can be seen that PE is indeed partially mediating the effects of both SRE and SI_IMG on BI as the strengths of both paths dropped while still being significant.

Unexpectedly, the researcher also found that PE maybe mediating fully, the relationship between EE → TandFC. This is proved by the fact that when a path existed between PE → TandFC, EE dropped out of significance, while previously, the path between EE and TandFC was significant. However, when both paths PE → TandFC and EE → TandFC exist, they are both insignificant. Therefore, the mediation effect of PE causes EE to drop out of significance. In the main model, no path was drawn between PE → TandFC. However, it was drawn here to test all paths with the mediators.

Mediator: V

The research investigated whether V is mediating any paths. Paths from PE and SI_IMG (IVs) to TandFC (DV) were investigated and only the PE —> TandFC path was significant. However, from the last comparison table in Appendix 19, it can be seen that the path PE —> TandFC dropped out of significance when the mediator was present and the mediated path was drawn. This confirms that V fully mediates the effect between PE and TandFC.

Mediator: TandFC

The research investigated whether TandFC is mediating any paths. From the tables in Appendix 19, it can be seen that only the paths from SRE and SI_IMG (IVs) to BI (DV) are significant when no mediators are present. Similarly, the path from PE (IV) to BI (DV) is significant and strong in the model with all the mediators. However, the path from PE (IV) to TandFC (M) is not significant. Similarly, the paths from SRE and SI_IMG (IVs) to TandFC (M) are not significant.

6.2.8.2 Bootstrapping approach

To reinforce and double-check the above findings, the researcher tested for mediation effects using bootstrapping within AMOS. Bootstrapping is a resampling method which is available within many SEM software, allowing researchers to use a larger sample that is derived from the original sample (Kline, 2012).

Using AMOS, the researcher performed a bootstrap using 1000 bootstrap samples and 95 bias-corrected confidence intervals. The following table summarises and shows the different relationships tested using the first approach (Baron and Kenny) and the Bootstrapping approach.

Relationship	Direct without Mediator	Direct with Mediator	Mediation Type (Baron and Kenny)	Bootstrapping Standardised Indirect effects
SI_IMG V TandFC	.134(.003)	-.015(.677)	**Full mediation**	.101(.001)
SI_IMG PE V	.208(***)	.151(***)	**Partial mediation**	.052(.001)
SI_IMG PE BI	.206(***)	.160(***)	**Partial mediation**	.054(.001)
SRE PE BI	.172(***)	.106(.018)	**Partial mediation**	.076(.001)
EE PE V	.125(.006)	.047(.301)	**Full mediation**	.072(.001)
EE PE BI	-.010(.809)	-.078(.057)	No mediation	.074(.002)
PE V TandFC	.232(***)	.031(.409)	**Full mediation**	.187(.001)
V TandFC BI	.131(.001)	-.006(.912)	**Full mediation**	.136(.003)

*** p-value < 0.01

Table 6.9 Mediation Effects

As shown above, Bootstrapping helps detect indirect effects and their significance. One noteworthy finding is the relationship EE PE BI which, according to the Baron and Kenny approach results above, had no mediation, but when bootstrapping was used, results shown a significant, although weak, indirect effect from EE to BI through PE. Perhaps because the mediation effect is very weak, the Baron and Kenny approach did not discover it.

6.3 Predicting Use

In this study, logistic regression was used to investigate to what extent BI and other constructs might predicts Use. Logistic regression was used because it was not possible to use SPSS AMOS to predict the binary value captured in the questionnaire which is associated with Use (dichotomous variable).

The researcher performed logistic regression analysis using SPSS with Use as the dependent variable, and BI, SRE, TandFC, BI, Exp, and THrs as independent variables (others were tested but dropped for having no effect). The full report can be seen in Appendix 20: Predicting Use.

A total of 497 cases were analysed and the full model significantly predicted use (chi-square = 85.535, df = 5, p < .0005). This model accounted for between 15.8% and 35.1% of the variance in use, with 99.1% of those who reported using innovations being predicted successfully. Only 25% of non-users were accurately predicted.

Overall, 92.6% of predictions were accurate in this model. By comparing the classification tables overall, there was an increase in what was initially expected that the model would be able to predict (91.1%).

Nagelkerke R Square = .351 indicating that the equation explained this much variance in the dependent variable.

The **Hosmer and Lemeshow Test** resulted in Chi-square value of 5.703 that is at a significance level of .680 indicating we have a great model with very good prediction. This Chi-square value being significant would indicate that there are misspecification issues in the predictive capacity of the model. Examining the contingency table for Hosmer and Lemeshow Test, we can see in the final category of predictive probabilities (row number 10) that with regarded to those using an innovation (IsAdopter = Yes column), the model expected 46.85 to be users while the observed shown 47 to be users. These numbers are very close and it proves that the predictive-ability of the model is excellent.

Correlations between predictor variables are also important to examine when looking at logistic and multiple regression in case of a suppressor effect. The following table shows the correlations between all the variables in the equation. Values in red are correlations with coefficients > 0.2 to pay attention to when explaining the probabilities of the values below, if any negative values for B were found.

Correlations

		Exp	THrs	SRE	TandFC	BI
Exp	Pearson Correlation	1	**.016**	**-.074**	**.119****	**-.125****
	Sig. (2-tailed)		.719	.097	.008	.005
THrs	Pearson Correlation	**.016**	1	**.095***	**.106***	**.217****
	Sig. (2-tailed)	.719		.033	.018	.000
SRE	Pearson Correlation	**-.074**	**.095***	1	**.179****	**.378****
	Sig. (2-tailed)	.097	.033		.000	.000
TandFC	Pearson Correlation	**.119****	**.106***	**.179****	1	**.270****
	Sig. (2-tailed)	.008	.018	.000		.000
BI	Pearson Correlation	**-.125****	**.217****	**.378****	**.270****	1
	Sig. (2-tailed)	.005	.000	.000	.000	

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

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

Table 6.10 Predicting Use: Correlations between Predictors

The table titled: “Variables in the Equation” available at the end of Appendix 20, shows the coefficients, the Wald statistic, associated degrees of freedom, and probability values for predictors. More importantly, it shows that SRE, TandFC, BI, Exp, and THrs are all predicting use.

Exploring the values of all significant coefficients reveal that while controlling for the other variables studied here:

- The probability of **Use** occurring is **1.867 more likely to happen** when **SRE increases one point** (95% CI 1.203 and 2.897).
- The probability of **Use** occurring is **1.474 more likely to happen** when **TandFC increases one point** (95% CI 1.092 and 1.989).
- The probability of **Use** occurring is **1.994 more likely to happen** when **BI increases one point** (95% CI 1.496 and 2.657).
- The probability of **Use** occurring is **2.296 more likely to happen** when **Exp increases one point** (95% CI 1.454 and 3.626).
- The probability of **Use** occurring is **2.303 more likely to happen** when **THrs increases one point** (95% CI 1.215 and 4.366).

6.4 Diagnostic & Assessment of the Models

It is important that researchers using SEM learn and try to assess their models.

One important recommendation given by experts and users of SEM (e.g. Byrne, 2010; Hair et al., 2010; Schumacker & Lomax, 2010) is that it is important to assess SEM models to ensure that developed models fit the data well.

In this section, the author will assess and diagnose some of the issues that may have surfaced while developing the structural models discussed in this chapter. Additionally, based on these assessments, one winning model would be selected

6.4.1 Normality assessment revisited

Results and tests carried out earlier shown some degree of non-normality in the data. Normality of that is an important assumption in SEM and non-normality of the data might lead to estimation inaccuracy in the structural models. In this section, the author would like to revisit a few issues just to be on the safe side.

While results from the normality assessment done in the multivariate assumptions section (section 5.8 above) indicated that non-normality were within the accepted range, results from the assessment of normality carried out using SPSS AMOS and presented in Appendix 10 indicated that there could be multivariate non-normality. Therefore, in this section, the author will check to see if there were any issues in model fit caused by such non-normality or if both models fit the data very well as reported earlier.

One approach to examining possible issues caused by multivariate non-normality if it existed is to make use of the bootstrapping technique. Bootstrapping can be used to evaluate estimates by computing standard errors that are not affected by non-normality. When using bootstrapping, estimates would be less biased and more accurate that the normal maximum likelihood estimation method if the distribution of the data was not normal (Byrne, 2010).

Using SPSS AMOS, the author will investigate both models using bootstrapping to see if there are significant differences between estimates and standard errors outputted using the maximum likelihood estimation (ML) method used in this chapter and between bootstrapped estimates which should give more accurate results if the data was significantly affected. Meaning, if there was a significant non-normality issue in the data, results from bootstrapped results (I.e. estimates and standard errors) should be significantly different.

Also, of noteworthy in the bootstrapping estimated output below is the column labelled ‘**bias**’. This is the difference between the maximum likelihood estimate and the bootstrap-based estimate. Therefore, a large value in the bias column indicates a significant discrepancy between both estimation methods.

Below are outputs for regression weights for both models. The aim is to investigate whether there are significant differences in estimates and errors as well as if there were high bias values indicating significant differences. The lack of high values in this column indicate that there are no significant differences between the bootstrapped estimation (which is appropriate when there are normality issues) applied in this section and the results and findings discussed previously throughout this chapter.

6.4.1.1 The Original Model (Model 1)

Comparing the coloured columns for both estimation methods reported in Appendix 23 show no significant differences between estimates (green) and standard errors (yellow). Moreover, there are no high values in both bias columns.

From the above, we conclude that this model was not impacted by non-normality and that results were not impacted by the possibility of multivariate non-normality and that it is likely that its influence, if any, was minimal.

6.4.1.2 The Post-Hoc Model (Model 2)

Comparing the coloured columns for both estimation methods reported in Appendix 24 show no significant differences between estimates (green) and standard errors (yellow). Moreover, there are no high values in both bias columns.

From the above, we conclude that this model was not impacted by non-normality and that results were not impacted by the possibility of multivariate non-normality and that it is likely that its influence, if any, was minimal.

6.4.2 Discrepancies Assessment & the Winning Model

Discrepancies between the estimated covariance model and the sample covariance model (I.e. The observed model) are captured in the residual covariance matrix reported by most SEM software packages (Byrne, 2010). Therefore, one possible way to assess SEM models is to investigate residuals. When investigating residuals, an upper cut-off point of 2.85 standardised residual value is suggested (Byrne, 2010). Any values above that indicate a significant discrepancy between the observed variables. Large values overall for the model indicate a critical issue in misspecification for the model while large residual values for certain variables indicate issues present in these variables (Schumacker & Lomax, 2010).

Investigating residuals (Appendix 21) for both models developed and tested in this chapter indicated that the post-hoc model is much better than the original model as it does not have residuals higher than the cut-off point. On the other hand, a number of significant discrepancies were found in the original model.

Based on the above, we conclude that the post-hoc model fits the data much better.

6.5 Summary

In this chapter aim was to develop the structural model which then could be used to test hypotheses postulated by the theoretical model developed in previous chapters of this study.

Based on the theoretical model proposed and discussed in previous chapters, the researcher developed the structural model from the measurement model that resulted from the previous chapter. Goodness-of-fit (GOF) indices indicated that the structural model fits the data very well. Based on this result, the researcher investigated the various paths drawn to confirm or reject proposed hypotheses. Additionally, the researcher tested the model under a number of moderated conditions using variables that were captured during the data collection stage.

Moreover, while examining the modification indices (MIs) output presented within SPSS AMOS, there were indications that there are further relationships that are worth exploring in the dataset. Keeping in mind these relationships suggestions, the author began a post-hoc analysis to uncover and test other logical relationships that may have never been tested before especially in this context. Based on post-hoc analysis, a number of significant and interesting relationships were found. Moderation testing was also done at this stage.

Furthermore, as a result of the post-hoc model having more than one dependent variable, it was possible to test for mediation effects in the post-hoc model. Mediation testing yielded some interesting results, some of which are reported for the first time.

Once analysis on both structural models was completed, the author assessed both models and found the post-hoc model to fit the data better and having no significant discrepancies. Additionally, the normality of the data was revisited to ensure that the data does not clearly violate the normal distribution assumption.

Lastly, as a result of being a dichotomous variable, to predict use, the researcher used a logistic regression to understand which variables help in predicting use. SRE, TandFC, BI, Exp, and THrs were found to be significant predictors of use.

To make it easier for the reader to follow and compare hypotheses testing results and other interesting relationships found, these are presented at the beginning of the next chapter.

7 Data Analysis

The aim in this chapter is to analyse the data resulting from the previous chapter and to discuss it in light of what is known in the literature. We start this detailed analysis by first summarising the key findings of this study. Then, we discuss the various constructs included and tested by both models (original and post-hoc). After that, moderation and mediation effects tested will also be discussed further.

7.1 Key Findings

Prior to discussing significant results obtained in more detail, they are briefly summarised and presented here.

7.1.1 Hypotheses

Hypotheses testing results across both structural models developed and used in this study are:

#	Hypothesis	Standardised Estimate Original Model	Standardised Estimate Post-Hoc Model	Remarks
H1	Performance Expectancy (PE) will have a significant positive influence on behavioural intention	0.291 ($p<0.001$) Supported	0.273 ($p<0.001$) Supported	
H2	Effort Expectancy (EE) will have a significant positive influence on behavioural intention	-0.072 ($p>0.05$) Not Supported	-0.066 ($p>0.05$) Not Supported	
H3	Social Influence (SI_IMG) will have a significant positive influence on behavioural intention	0.135 ($p<0.05$) Supported	0.165 ($p<0.001$) Supported	Weak effects
H4a	Facilitating Conditions (TandFC) will have a significant positive influence on behavioural intention	0.157 ($p<0.05$) Supported	0.19 ($p<0.001$) Supported	Weak effects
H4b	Facilitating conditions (TandFC) will have a significant positive influence on actual use	Supported. Tested using Logistic Regression		
H5a	Results demonstrability (RD) will have a significant positive influence on Behavioural intention			Dropped from the study
H5b	Results demonstrability (RD) will have a significant positive influence on performance expectancy			Dropped from the study
H6	Visibility (V) will have a significant positive	-0.016 ($p>0.05$)	Relationship dropped in post-	

	influence on behavioural intention	Not Supported	hoc model	
H7	Trialability (T) will have a significant positive influence on behavioural intention			Merged with FC
H8	Reinvention (ReInv) will have a significant positive influence on behavioural intention	0.187 (p<0.001) Supported	0.182 (p<0.001) Supported	Weak effects
H9	Students' requirements (SRE) and expectations will have a significant positive influence on behavioural intention	0.147 (p<0.05) Supported	0.13 (p<0.05) Supported	Weak effects
H10	Students' learning (SL) will have a significant positive influence on behavioural intention	0.001 (p>0.05) Not Supported	Dropped in post-hoc model	
H11	Behavioural intention (BI) will have a significant positive influence on actual use	Supported. Tested using Logistic Regression		

Table 7.1 Summary of Hypotheses Testing Results

7.1.2 Interesting Relationships

Additionally, a number of interesting relationships were found. These are:

Relationship	**Standardised Estimate** **Post-Hoc Model**	**Literature Support (if any)**
PE —> V	0.253 (p<0.001)	
EE —> PE	0.243 (p<0.001)	Lin and Lu, 2000; Martins and Kellermanns, 2004; Sun and Zhang, 2006; Saade, Nebebe, and Tan, 2007
SI_IMG —> PE	0.178 (p<0.001)	Venkatesh and Davis, 2000; Martins and Kellermanns, 2004; Sun and Zhang, 2006; Schepers and Wetzels, 2007; Jonas and Norman, 2011
SI_IMG —> V	0.142 (p<0.05)	

V —> TandFC	0.598 (p<0.001)	
SRE —> PE	0.256 (p<0.001)	

Table 7.2 Interesting relationships

7.1.3 Moderation Effects

Moderating testing was done on both models developed and empirically tested by this study. Moderating variables tested for moderation effects are: gender, age, experience, education, voluntariness, teaching hours, and country.

A number of significant moderating effects were found. The following table summarises these effects:

	Gender	**Age**	**Experience**	**Teaching hours**	**Voluntary**	**Country**
TandFC → BI		Significant and stronger for younger staff (30-50 years old) #1.		Significant and stronger for those teaching less (51-500 hrs./yr.) #2.	Significant for both groups but stronger for those conforming to mandated adoption #2.	Significant for England and Scotland but stronger for the latter group #2.
RelInv → BI	Significant and **stronger for males** #1. Significant for both groups but **stronger for males** #2.				Significant and stronger for those adopting by themselves #2.	Significant for England and Scotland but stronger for the first group #2.
SRE → BI			Significant and stronger for more experienced staff with (+9 years of work experience) #2.	Significant and stronger for those **teaching more** (501-1000 hrs./yr.) #2.		

V → TandFC		Significant for both groups but stronger for **younger staff** (30-50 years old) [#2].				
SI_IMG → V	Significant and stronger for females [#2].	Significant and stronger for **younger staff** (30-50 years old) [#2].		Significant and stronger for those **teaching more** (501-1000 hrs./yr.) [#2].		Significant and stronger for those from **England** [#2].
PE → V						Significant for all groups but stronger for those from Wales [#2].
SRE → PE		Significant for both groups but stronger for **younger staff** (30-50 years old) [#2].				
EE → PE			Significant for all groups but stronger for less experienced staff (less than 9 years of work experience) [#2].			Significant for all groups but stronger for those from **England** [#2].
SI_IMG → PE			Significant for more experienced staff (+5 years of work experience). Stronger for those with 5-9 years of experience [#2].			

[#1]: Original model. [#2]: Post-Hoc model.

Table 7.3 Summary of Moderating Effects

7.1.4 Mediation Effects

Mediation testing was done on the post-hoc model as it has a number of dependent variables. Full and partial mediation effects were uncovered. The following table summarises these influences:

Relationship	**Mediation Type**	**Bootstrapping** **Standardised Indirect effects**
SI_IMG V TandFC	**Full mediation**	.101(.001)
SI_IMG PE V	Partial mediation	.052(.001)
SI_IMG PE BI	Partial mediation	.054(.001)
SRE PE BI	Partial mediation	.076(.001)
EE PE V	**Full mediation**	.072(.001)
EE PE BI	Partial mediation	.074(.002)
PE V TandFC	**Full mediation**	.187(.001)
V TandFC BI	**Full mediation**	.136(.003)

*** p-value < 0.01

Table 7.4 Summary of Mediation Effects

7.2 Constructs of the model

Aside from the constructs that were dropped (SI_INF and RD), as explained in chapter 5, the following is a discussion of the results related to the constructs and any relationships between them investigated in this study.

7.2.1 Performance Expectancy (PE)

Performance Expectancy (PE) is a construct in UTAUT that was constructed based on a number of similar constructs in different theories including the widely used construct of perceived usefulness (PU).

Perceiving the technology (or innovation) as beneficial to the individual adopter's work encourages the likelihood of using it (Kumar et al., 2008; Mitra, Hazen, LaFrance, & Rogan, 1999; Rogers, 2003). This attribute is referred to by the diffusion of innovation theory as relative advantage (Rogers, 2003).

Many studies found PE to be a significant predictor of BI. Schepers and Wetzels' (2007) meta-analysis showed that PU had a significant effect on attitude and BI. Sun and Zhang (2006) in their review of a number of studies found that in 71 out of 72 studies, PU mostly had a significant influence on attitude, BI, or actual use. Similarly, other studies (Chau & Hu, 2002; El-Gayar & Moran, 2006; Jong & Wang, 2009; Lakhal et al., 2013; Lee et al., 2005; Liu et al., 2005; Martins & Kellermanns, 2004; Oye et al., 2012b; Selim, 2003; Venkatesh & Davis, 2000; Yamin & Lee, 2010) also found that PE or PU had a significant effect on BI. In the same vein, Kumar et al. (2008) found that PU was a significant predictor of actual use of computer.

Furthermore, a Delphi study by Hazen et al. (2012) found that the relative advantage (similar to PU and PE) of the innovation is one of the key factors influencing the adoption of educational innovations.

In comparison, in the study of Saade et al. (2007), PU had no significant direct effect on behavioural intention. This may have been the case because their model included attitude towards use as a predictor of behavioural intention, and it may have played a mediating role or could explain most of the variance that may have been captured by perceived usefulness when this construct is absent. This was also the case in some other studies (Boontarig, Chutimaskul, Chongsuphajaisiddhi, & Papasratorn, 2012; Park, 2009; Sumak et al., 2010). For instance, Sumak et al. (2010) found that PE had a significant impact on attitude towards using Moodle (a learning management system) rather than behavioural intention.

In this study, and consistent with the first group of studies discussed above, PE was found to be a significant predictor of BI (b*= 0.291, $p < 0.001$), the strongest of all the predictors. Analysis of the post-hoc model reinforced this finding (b*= 0.273, $p < 0.001$). This indicates that PE significantly and positively influences BI. Therefore, this indicates that the higher the perception of usefulness of the innovation, the higher will be the intention to adopt it.

Furthermore, analysis of the post-hoc model reveals that PE is a significant predictor of Visibility (V) as a dependent variable (b*= 0.253, $p < 0.001$). This indicates that the higher the perception of usefulness of the innovation, the more likely individuals would expect it to be visible (i.e. used by others). While the author found no other studies that investigated this relationship, the relationship between PE and V seemed logical but it could perhaps be interpreted both ways. This means that, in addition to the relationship PE → V being suggested by SPSS AMOS, V → PE was also suggested. Logically speaking, both relationships sound logical. V → PE, could thus be explained: the more visible an innovation or technology is perceived to be, the higher its perceived usefulness and performance gain on the job. The decision of whether to draw PE → V or V → PE was solely based on the strength of the relationship. There was a slight difference in the strength of the PE → V relationship, and the overall model fit was slightly better.

7.2.2 Effort Expectancy (EE)

Effort Expectancy (EE) is a construct in UTAUT that was constructed based on a number of similar constructs in different theories including the widely used construct of perceived ease of use (PEOU).

There seems to be some inconsistencies with regard to the influence of EE or PEOU on BI (Sun & Zhang, 2006) or its influence on perceived usefulness (performance expectancy).

TAM posited that perceived ease of use was a significant predictor of perceived usefulness. This is supported by others (Lin & Lu, 2000; Martins & Kellermanns, 2004; Saadé et al., 2007). Sun and Zhang (2006) found that in 43 out of 50 studies reviewed, the link between PEOU to PU is significant. An exception to this was found by Chau and Hu (2002), as PEOU had no effect on PU. A possible explanation, the authors noted, is that professionals with relatively high intellectual capacity are less likely to give much weight to the ease of use.

Regarding **EE postulated influence on PE** in this study, the relationship was tested in the post-hoc model and results show EE to be a significant and strong predictor of PE ($b^* = 0.243$, $p < 0.001$). This is consistent with many of the studies discussed above.

Similarly to Chau and Hu (2002), respondents surveyed in this research were also professionals (academic staff members) who certainly have a relatively high intellectual capacity. However, in contrast to the results of participants giving less weight to EE, the path from EE to PE was found to be significant in the second post-hoc model.

Regarding **EE's influence on BI**, Venkatesh et al. (2003) did not find any direct effects between perceived ease of use towards behavioural intention after the implementation of innovation or technology. This means that the construct had a direct effect only prior to the implementation or adoption of the technology or innovation in question. Similarly, other studies did not find a significant influence of EE (or PEOU) on BI (Jong & Wang, 2009; Park, 2009;

Sumak et al., 2010). Also, Selim (2003), in his study of course website acceptance, found that ease of use had an insignificant direct effect on intention to use, which he termed CWUSE. However, he found that ease of use had a significant indirect effect on intention that is mediated through perceived usefulness.

In contrast, Schepers and Wetzels' (2007) meta-analysis showed that PEOU had a significant effect on attitude and BI. This was in line with Venkatesh and Davis (2000) who reported that PEOU was a significant predictor of intention across four studies. Other studies also found that EE or PEOU influences or is positively correlated with BI (Boontarig et al., 2012; El-Gayar & Moran, 2006; Martins & Kellermanns, 2004; Oye et al., 2012b; Yamin & Lee, 2010). In the same vein, Kumar et al. (2008) found that PEOU was the strongest predictor of actual use of computer.

In this study and consistent with some of the previous studies above, EE was not a significant predictor of BI. Analysis of the post-hoc model reinforced this finding.

7.2.3 Social Influence (SI)

Social Influence (SI) is a construct in UTAUT that incorporates a number of similar constructs in different theories including: subjective norm (SN), social factors, and image.

The UTAUT posited SI as a predictor of BI. Similarly, other studies found a significant influence of SI (from peers or friends, etc.) on BI, attitude, user acceptance, technology use, or diffusion in general (El-Gayar & Moran, 2006; Hsu, 2012; Jacobsen, 1998; Jong & Wang, 2009; Lakhal et al., 2013; Oye et al., 2012a, 2012b; Roberts et al., 2007; Sumak et al., 2010; Venkatesh & Davis, 2000). However, as noted by Sun and Zhang (2006) in their review of a number of studies, there are inconsistencies which might be caused as a result of SN (social influence in this study) capturing or being related to different mechanisms such as compliance or altering the user's own belief as a result of others' opinions or influences.

The reviews of different studies by Sun and Zhang (2006) and Schepers and Wetzels (2007) showed that SN had a significant influence on perceived usefulness and behavioural intention in a number of studies. Others (e.g. Grandon, Alshare, & Kwun, 2005; Park, 2009) reported similar findings. Venkatesh and Davis (2000) found that SN has a significant effect on perceived usefulness especially when the user has low or no prior experience with the technology. Similarly, Martins and Kellermanns (2004) found that peer encouragement (a form of social influence) had a significant and strong effect on perceived usefulness in their study of students' acceptance of a web-based course management system. In the same vein, Tabata and Johnsrud (2008) found that the possibility of improving self-image as a result of participating in distance education would increase the likelihood of participating.

In contrast, Chau and Hu (2002) found SN to have a non-significant effect on BI. They attribute this to the fact that physicians are likely to carry their own evaluations rather than give weight to others' opinions. Similar results with regard to the absence of any influence of SN on BI were reported by others (Boontarig et al., 2012; e.g. Venkatesh et al., 2003).

Moreover, while studying the influence of image (a construct that is incorporated in SI), Moore and Benbasat (1991) found image to be a weak predictor of adoption in their study.

In this study, SI (SI_IMG construct) was found to be a significant predictor of BI ($b^* = 0.135$, $p < 0.01$). Analysis of the post-hoc model reinforced this finding, although this time, the relationship was slightly stronger and more significant ($b^* = 0.165$, $p < 0.001$). These influences are weak. This may be similar to what Moore and Benbasat (1991) found.

Respondents surveyed in this research are expected to carry their own evaluations as academic members of staff who mostly, have some autonomy and freedom when it comes to using technologies or innovations that are at their disposal. However, unlike Chau and Hu (2002) and consistent with a number of studies in the field, the SI → BI path was found to be significant, although weak, in both of the models tested in this study. This indicates that members of staff give low weight to the influence of others on their decisions, although there is still some influence. Still, however, they are not influenced easily by others. One possible explanation might be what Chau and Hu (2002) argued, that academic members of staff are not usually and easily influenced by peers that much, but, instead, they evaluate and choose what technology or innovation is appropriate.

Moreover, the significant influence of SI on PE ($b^* = 0.178$, $p < 0.001$), which was tested in the post-hoc model, indicates that the higher the influence by others to use a certain innovation or technology, the more likely are individuals to form a favourable perception of its usefulness. This is in line with some studies mentioned above (Jonas & Norman, 2011; e.g. Martins & Kellermanns, 2004).

Furthermore, the significant influence of SI on V ($b^* = 0.142$, $p < 0.01$), which was tested in the post-hoc model, indicates that the stronger the influence by peers, the more likely that individuals who are influenced expect to see the innovation being used by others.

Lastly, in contrast to the findings of Venkatesh et al.'s (2003), social influence was found to be significant when adoption was voluntary and not significant when adoption was mandated. Further discussion follows when considering moderators (section 7.3.5 below Voluntariness below).

7.2.4 Reinvention (ReInv)

Hazen et al. (2012) in their study found that the ability to adapt or modify innovations to suit adopters' needs was an important factor influencing the adoption of educational innovations. This is in line with Rogers (2003), who argued that innovations that are flexible can be adapted and used more easily in a wider range of conditions.

In this study and consistent with Rogers (2003) and Hazen et al. (2012), ReInv was found to be a significant predictor of BI ($b^* = 0.187$, $p < 0.001$). Analysis of the post-hoc model reinforced this finding ($b^* = 0.182$, $p < 0.001$).

Such results indicate that ReInv significantly and positively influences the BI of individuals and that the more it is perceived an innovation or technology can be changed or modified to suit the adopter's needs, the higher the intention to adopt would be.

7.2.5 Students Requirements and Expectations (SRE)

In this study the students' requirements and expectations (SRE) construct was found to be a significant predictor of BI ($b^* = 0.147$, $p < 0.05$). Analysis of the post-hoc model reinforced this finding ($b^* = 0.13$, $p < 0.05$) and also showed SRE as a significant predictor of the dependent variable PE ($b^* = 0.256$, $p < 0.001$).

Such results indicate that SRE significantly and positively influences the BI of individuals and that the higher the perception that an innovation or technology helps meet or exceed students requirements and expectations, the higher the intention to adopt. However, the effects are not that strong in both models.

Moreover, the significant influence of SRE on PE, which was tested in the post-hoc model, indicates that the higher the perception that an innovation or technology helps meet or exceed students' requirements and expectations, the higher its perceived usefulness.

Furthermore, SRE was found to help explain some of the variance in use (see 6.3

Predicting Use). Therefore, SRE is not only influencing BI, it is also influencing use directly, as suggested by the data and the tests.

Lastly, investigating significant moderation effects in the post-hoc model uncovered some interesting findings with regard to work experience and teaching hours as moderators. This is illustrated below (Figure 7.1).

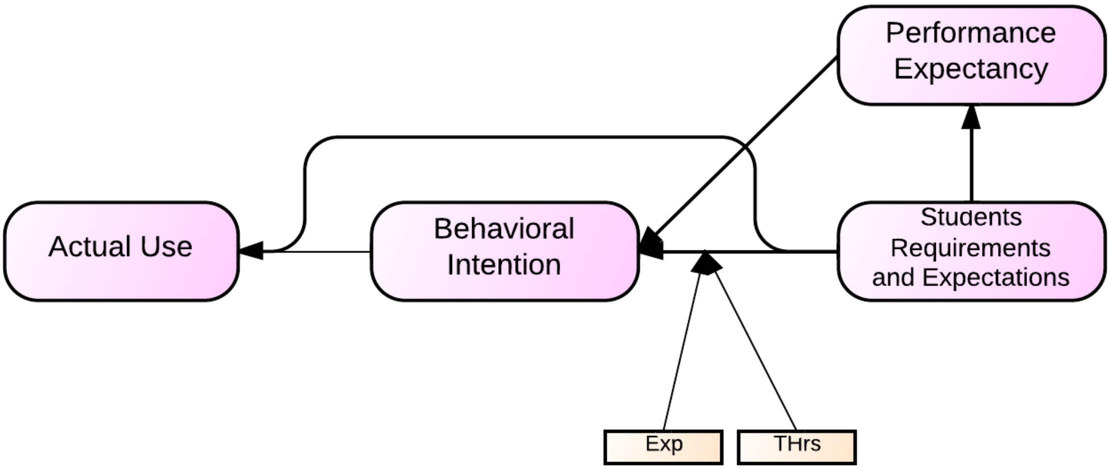

Figure 7.1 Investigating Exp and THrs as Moderators for SRE on BI

First, the influence of SRE on BI, discussed above, although weak, is moderated (when tested individually) by work experience and teaching hours such that any increase in those moderating variables (Exp or THrs) results in an increase in the influence of SRE on BI. Put differently, those with more work experience or teaching hours give more importance to SRE. Second, as mentioned above, SRE also influences Use directly increasing the likelihood of Use (i.e. adoption) happening. Third, SRE influences BI indirectly through PE as a mediator. PE is acting as a partial mediator for SRE —> BI.

In attempting to explain what is happening, the researcher reached two different and very contradicting possibilities.

The first possibility is that as members of staff gain experience, which is also gained by teaching more, they become aware of the importance of meeting and exceeding students' requirements. Therefore, when thinking about adopting an innovation, they are conscious about the importance of adopting and using innovations that would result in a positive outcome with regard to meeting or exceeding students' requirements. They may pursue and test other innovations to further exceed students' requirements and expectations.

The second possibility, which raises some concerns, is that as experience increases, staff members become aware of the fact that they only need to meet students' requirements because it is a university requirement. In this case, staff members are conforming to university standards. They adopt and use innovations that help them conform to these rules. They may not pursue or go after and use other innovations. Instead, they do the bare minimum to conform to the standards in place.

Based on the above, it can be seen that proposing SRE and developing some measures to measure for it was indeed a good decision. SRE is influencing a number of factors as shown above. Perhaps of most importance with regard to SRE is that it influences both BI and use directly and indirectly. However, there is need for further research to confirm or add to the findings of this study; to determine whether such influences are specific to this study (e.g. might be applicable within the UK only or within certain parts).

7.2.6 Students Learning (SL)

There is and should be one ultimate goal for the diffusion and use of innovations or technologies in universities, to focus on students' learning through a student-learning centred paradigm shift that focuses on improving students' learning rather than the ability to teach the masses by faculty members (Miller et al., 2000).

The introduction of technologies and innovations in universities can certainly encourage staff members to re-evaluate what they offer (e.g. curriculum, instruction methods, etc.) and to facilitate a technology-enabled instruction that is student-oriented (Miller et al., 2000).

Student-oriented quality education is what society expects from universities; after all, education is one of its core missions (Modernization of Higher Education Group, 2013).

Despite the literature suggesting that students' learning is one of the primary reasons for using innovations in the classroom (Peluchette & Rust, 2005; Roberts et al., 2007; Spodark, 2003), in this study, students' learning (SL) is not a significant predictor of BI ($b^* = 0.001$, $p > 0.05$).

Such a finding is intriguing as it would be expected that academic staff members would give weight and importance to students' learning and, therefore, use innovations and technologies that may help improve students' learning.

Such a result may be similar to the findings of Peluchette and Rust (2005) that only 25% of staff indicated that the decision of what instructional technology to use is influenced by students' learning.

Trying to explain this finding resulted in a number of possibilities some of which might be of concern. First, it is possible that academic members of staff regard students' learning as something they do not need to worry about especially since there are no clear and solid ways to measure them. After all, low marks achieved by students are usually attributed to the students' low performance or inability to perform. This may also explain why SRE was found to be significant, unlike SL, as there are usually processes in place that help ensure that minimum requirements and expectations are fulfilled by academic members of staff. Therefore, this may indicate that SL is perceived as an additional effort that is not required.

Second, it is possible that academic members of staff perceive themselves as experienced in what can and cannot help their students. Therefore, if they see innovations or technologies, they evaluate them based on factors other than their potential impact on students. For instance, it may be that they evaluate the innovation or technology from a performance gained perspective - Would this innovation or technology help reduce my workload and relieve my pressures or help me in completing my tasks faster?

Third, similar to the above explanation, it is possible that members of staff, as a result of being pressured, do not give much weight to innovations that can potentially impact students' learning because they know that adopting and using such innovations or technologies would probably require initial time or resources investment, adding more to their many commitments.

Lastly, it could be that despite the measures' reliability and validity, further development should go into ensuring that these measures are clear to participants.

Still however, the author was expecting SL to have at least some minimal influence on BI, even if on a similar level to SRE. The absence of such influence, although due to any or all of the reasons discussed above, was unexpected.

7.2.7 Visibility (V)

In contrast to some previous discussions (Rogers, 2003; Wejnert, 2002), visibility (V) was not found to be a significant predictor of BI ($b^* = -0.016$, $p > 0.05$). However, the significant and strong influence of V on TandFC, which was tested in the post-hoc model, indicates that visibility could also influence BI indirectly through TandFC. Investigating the indirect effects table reported in Appendix 16 provides evidence that such influence exists.

The relationship V → TandFC was suggested by SPSS AMOS and it is also logically sound; the more the innovation is perceived to be visible, the more it is expected that there are facilitating conditions in place to support its widespread adoption and use.

7.2.8 Trialability and Facilitating Conditions (TandFC)

Facilitating conditions (FC) is a construct in UTAUT that was constructed based on a number of similar constructs in different theories including: perceived behavioural control, and compatibility.

In this study, initially, Trialability (T) and Facilitating Conditions (FC) were considered as two separate constructs. However, during the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) carried out by the researcher, both constructs were found to measure the same thing. Hence, the resulting construct was named TandFC and referred to as facilitating conditions generally since it is a more general term than trialability.

One possible reason why T and FC were measuring the same factor can be possibly understood when taking into consideration what both constructs aim to explain and how they are defined. Rogers (2003) stressed the importance of reducing the complexity of innovations and offering needed support to help reduce uncertainties or worries. This was echoed by Shea, Pickett, and Li (2005).

Moreover, Moore and Benbasat (1991) defined trialability as: "the degree to which an innovation may be experimented with before adoption". Rogers (2003) also discussed the importance of being able to try or trial the innovation or technology beforehand in order to be able to understand it fully. Experimenting with an innovation beforehand certainly helps reduce uncertainties or worries adopters may have as they would be able to gain first-hand experience and knowledge of how the innovation could be used and its potential impact.

Tabata and Johnsrud (2008), in their study of participation in distance education found that the ability to try-out distance education before making a decision to use it was significantly and positively associated with the increased likelihood of participating.

It may very well be that T is strongly related to FC and that it helps explain a part of the FC construct.

The UTAUT posited FC as a predictor of actual use, arguing that it becomes insignificant in predicting intention if both PE and EE constructs are present (Al-Shafi, 2009; Venkatesh et al., 2003). This was not the case in this study.

Furthermore, some studies reported that FC influences actual use (Oye et al., 2012a; e.g. Sumak et al., 2010). Others confirmed that it can have a significant effect BI (Jong & Wang, 2009; Lakhal et al., 2013). Hazen et al. (2012) found facilitating conditions to be one of the most important factors influencing the adoption of educational innovations. In contrast, Hsu (2012) found that FC did not have a significant on over acceptance or use while claiming that this was the case as a result of the context, Taiwan, being an advanced information infrastructure community.

In this study, in contrast to two studies reported above (Al-Shafi, 2009; Venkatesh et al., 2003), TandFC was found to be a significant, although not strong, predictor of BI ($b^*= 0.157$, $p < 0.05$). Analysis of the post-hoc model reinforced this finding ($b^*= 0.19$, $p < 0.001$). Such a finding is consistent with some previous studies (e.g. Jong & Wang, 2009; Lakhal et al., 2013). These results indicate that TandFC significantly and positively influences the BI of individuals and that, the higher the perception of the availability of facilitating and supporting conditions (TandFC) that support the innovation, the higher the intention to adopt it will be. However, since the path is not strong, this may suggest that what Venkatesh et al. (2003) noted may be present here and that the path is weak as a results of PE and EE both being present.

Moreover, this study tested the influence of TandFC on Use. Previous studies have shown that FC has a significant influence on use (Oye et al., 2012a; Sumak et al., 2010; Venkatesh et al., 2003). Consistent with these studies, TandFC was found to influence use (see 6.3

Predicting Use).

Based on the above, it can be seen that TandFC is actually influencing both BI and Use. Therefore, facilitating conditions should be provided to support and help in the adoption and use of innovations.

7.2.9 Behavioural Intention (BI) and Use

Both TRA and TAM postulated that behavioural intention (BI) is a key determinant of use. Many found that BI correlated significantly with use or predicted it (Davis et al., 1989; Jong & Wang, 2009; Sumak et al., 2010; Turner et al., 2010). Venkatesh et al. (2003) argued that if the values of the four key constructs of PE, EE, SI, and, FC are higher, the value of BI is higher and so is the acceptance of the technology.

In this study, after applying logistic regression to study the influence of the various constructs on use, only SRE, Exp (moderator), THrs (moderator), FC and BI were found to have an influence on use. This means that, they explain some of the variance in use.

7.3 Moderators

Many studies sought to understand the influence of demographics on adoption (Davis et al., 1989; Kijsanayotin et al., 2009; Moore & Benbasat, 1991; Quazi & Talukder, 2011; Sun & Zhang, 2006; Venkatesh et al., 2003; Venkatesh & Morris, 2000; Wu & Lederer, 2009). Understanding moderation effects is important when studying adoption or acceptance as they could have a profound effect (Sun & Zhang, 2006).

The study aimed to study the influence of a number a moderators. These moderators are: **gender**, **age**, **work experience**, **voluntariness of use**, **level of education (qualification)**, the number of **teaching hours**, and **country**. It is important to note the difference between experience as used in previous studies indicating the years of experience of using the technology or innovation and the work experience factor considered in this study.

The focus in this section is on moderation effects with significant influences. Moderation effects with lesser possible influences have already been briefly discussed (see 6.1.3.2 and 6.2.7.2 above).

7.3.1 Gender

Some studies investigating innovation or technology adoption have found that gender moderates the relationship between a number of constructs (e.g. V Venkatesh & M. Morris 2000; Venkatesh et al. 2003; Peluchette & Rust 2005; Sun & Zhang 2006).

The results of the moderation testing on both models analysed in this study showed that gender moderated the **ReInv → BI** relationship in the first model, suggesting that males give more weight to ReInv. This means that males regard the ability to modify, tweak, or change the innovation to suit their needs as important. Therefore, the ability (or inability) to reinvent or modify the innovation should be made clear to male academic members of staff in particular.

Unlike previous studies, no significant moderation effect by gender was found on the relationships between PE, EE, or SI and BI.

7.3.2 Age

Some studies investigating innovation or technology adoption have found that age moderates the relationship between a number of constructs (Kumar et al., 2008; e.g. Venkatesh et al., 2003).

The results of the moderation testing done on both models analysed in this study showed that age moderated the **TandFC → BI** relationship in the first model, suggesting that younger academics give more weight to TandFC. This means that younger members of staff are more concerned about the facilitating and supporting conditions available to support them if they decide to use a particular innovation. Therefore, facilitating and supporting conditions should be put in place and made clear especially to younger members of staff as it seems that the influence fades as age increases.

Additionally, it was found that age moderated the **SRE → PE** relationship in the post-hoc model, suggesting that younger members of staff give more weight to SRE. This means that younger members of staff are more concerned about students' requirements and expectations and that they perceive as more useful innovations that can help them meet or exceed students' requirements and expectations. Therefore, students' requirements and expectations should be made clear, how members of staff can meet them, and what innovations can help in exceeding those expectations.

Moreover, it was found that age moderates the **SI_IMG → V** relationship in the post-hoc model, suggesting that younger members of staff give more weight to SI_IMG. This means that younger staff members' perception of the visibility of the innovation is influenced more by social influence. Therefore, keeping in mind the visibility of the innovation as an important factor, staff members should be encouraged to share their positive experiences with using any innovations, in order to create a positive influence on others.

Lastly, it was found that age moderates the **V → TandFC** relationship in the post-hoc model, suggesting that younger staff members give more weight to V. This means that younger staff members' perception of the facilitating and supporting conditions is influenced more by the degree to which they perceive the innovation as being more visible. Therefore, successful experiences and attempts at using various innovations should be disseminated to create a favourable perception of the support provided for members of staff to use such innovations.

All of the aforementioned moderation effects by age seemed mostly to influence younger staff members to give more weight to all of the relationships.

7.3.3 Experience (Work Experience)

The results of the moderation testing on both models analysed in this study showed that experience moderates the **SI_IMG → PE** relationship in the post-hoc model, suggesting that academic staff members with moderate experience (5-9 years) give more weight to SI_IMG. This means that for those staff with moderate experience, the perception of the usefulness and performance gain associated with using an innovation is influenced more by the perceived social influence. Therefore, staff members should be encouraged to share their positive experiences of using any innovations, to create a positive influence on others.

Additionally, it was found that experience moderates the **EE → PE** relationship in the post-hoc model, suggesting that staff members with less experience (less than 5 years) give more weight to EE. This means that for those staff with less experience, the perception of usefulness and performance gain associated with using an innovation is influenced more by the perception of its effort expectancy. Therefore, being aware of the effort needed to use an innovation is of high importance especially to those with less experience.

Moreover, it was found that experience moderates the **SRE → BI** relationship in the post-hoc model, suggesting that staff members with more experience (more than 9 years) give more weight to SRE. This means that for those with more experience, the intention to use an innovation is more influenced by their perception of how it can help meet or exceed students' requirements and expectations. Therefore, students' requirements and expectations should be made clear, how members of staff can meet them, and what innovations can help in exceeding those expectations. Such a result may also indicate that as staff members gain more work experience, they become more familiar with their students' requirements and expectations. Therefore, being more inclined to use innovations that can help them meet or exceed those requirements and expectations.

7.3.4 Education

The results of the moderation testing on both models analysed in this study showed that there were no significant moderation caused by the education level (i.e. qualification). However, there were some non-significant but still noticeable influences that may have been caused by education as a moderator. These were mentioned in the previous chapter.

7.3.5 Voluntariness

Some studies investigating innovation or technology adoption have found that voluntariness moderates the relationship between some constructs (Moore & Benbasat, 1991; Sun & Zhang, 2006; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Wu & Lederer, 2009).

The results of the moderation testing on both models analysed in this study showed that voluntariness moderates the **ReInv → BI** relationship in the post-hoc model, suggesting that in voluntary adoption settings, staff members give more weight to ReInv. This means that, staff members who are adopting innovations of their own free-will perceive the ability to modify or change the innovation to suit their needs as more important. Therefore, helping members of staff understand what can and cannot be done with a certain innovation may influence their intention to use it if, it can be modified to suit their needs.

Moore and Benbasat (1991) argued for the importance of trying innovations before fully adopting and using them for those doing so out of their own voluntary decision. It is likely that reinvention is also important for this group of adopters. For instance, it could be that trying an innovation before fully adopting it allows adopters to test first-hand whether the innovation could be modified to suit their needs.

Additionally, it was found that voluntariness moderates the **TandFC → BI** relationship in the post-hoc model, suggesting that in mandatory adoption settings, staff members give more weight to TandFC. This means that if the adoption of a certain innovation is mandatory, members of staff who are responding and adopting the innovation perceive the need for facilitating and supporting conditions as more important. Therefore, if the adoption of a certain innovation is mandatory, the facilitating and supporting conditions for such innovation should be in place and clearly communicated to all adopters. Certainly, this is logical and expected since any organisation wishing to mandate the use of a certain innovation or technology should, without a doubt, make sure that all facilitating and supporting conditions are in place to encourage wider adoptions.

Lastly, the results of moderation testing on both models showed that, in contrast to the study of Venkatesh et al. (2003), social influence (SI_IMG) was in fact significant when adoption of the innovation was voluntary rather than when adoption was mandated. This was also the case with the SI_IMG → V relationship as it was significant when adoption was voluntary and insignificant when adoption was mandatory.

7.3.6 Teaching Hours

The results of the moderation testing on both models analysed by in study showed that teaching hours moderates the **SI_IMG → V** relationship in the post-hoc model, suggesting that staff members with more teaching hours give more weight to SI_IMG. This means that the perception of the visibility of a certain innovation for those with more teaching hours is influenced more easily by what others say or indicate (social influence). Therefore, keeping in mind the visibility of the innovation as an important factor, members of staff should be encouraged to share their positive experiences with using any innovations, in order to create a positive influence on others.

Additionally, it was found that teaching hours moderates the **SRE → BI** relationship in the post-hoc model, suggesting that staff members with more teaching hours give more weight to SRE. This means that for those with more teaching hours, the intention to use an innovation is more influenced by their perception of how it can help meet or exceed students' requirements and expectations. This is similar to the case with work experience as a moderation discussed above. Teaching more hours surely contribute to the experience gained by the staff member. Therefore, similar to what was discussed above (section 7.3.3), it should be clear how staff members can contribute to meeting or exceeding students' requirements and expectations.

Moreover, it was found that teaching hours moderates the **ReInv → BI** relationship in the post-hoc model, suggesting that staff members teaching fewer hours give more weight to ReInv. This means that those with fewer teaching hours regard the ability to modify, tweak, or change the innovation to suit their needs as important. Therefore, helping staff members understand what can and cannot be done with a certain innovation may influence their intention to use it, if it can be modified to suit their needs.

Lastly, it was found that teaching hours moderates the **SI_IMG → BI** relationship in the post-hoc model, suggesting that staff members teaching fewer hours give more weight to SI_IMG. This means that for those staff with fewer teaching hours, the intention to use a certain innovation is influenced more by the perceived social influence. Therefore, staff members should be encouraged to share their positive experiences with using any innovations, to create a positive influence on others.

7.3.7 Country

The results of the moderation testing on both models analysed in this study showed that the country moderates the **EE → PE** relationship in the post-hoc model, suggesting that staff members from England give more weight to EE. This means that for those staff from England, the perception of usefulness and performance gain associated with using an innovation is influenced more by the perception of its effort expectancy. Therefore, being aware of the effort needed to use an innovation is of high importance.

Additionally, it was found that the country moderates the **SI_IMG → V** relationship in the post-hoc model, suggesting that staff members from England give more weight to SI_IMG. This means that for those from England, the perception of the visibility of the innovation is influenced more by any social influence. Therefore, keeping in mind the visibility of the innovation as an important factor, members of staff should be encouraged to share their positive experiences with using any innovations, to create a positive influence on others.

Moreover, it was found that the country moderates the **TandFC → BI** relationship in the post-hoc model, suggesting that staff members from England and Scotland give more weight to TandFC, and the latter, give even more weight. This means that those from England and Scotland perceive the need for facilitating and supporting conditions as more important. Therefore, facilitating and supporting conditions for the use of innovations should be in-place and clearly communicated to all adopters.

Furthermore, it was found that the country moderates the **ReInv → BI** relationship in the post-hoc model, suggesting that staff members from England and Scotland give more weight to ReInv, although the first, give more weight. This means that those from England or Scotland regard the ability to modify, tweak, or change the innovation to suit their needs as important. Therefore, helping members of staff understand what can and cannot be done with a certain innovation may influence their intention to use it if it can be modified to suit their needs.

Lastly, it was found that the country moderates the **PE → V** relationship in the post-hoc model, suggesting that staff members from Wales give more weight to PE. This means that for those from Wales, the perception of the visibility of the innovation is influenced more by the perceived usefulness or performance gain of the innovation. Therefore, keeping in mind the visibility of the innovation as an important factor, members of staff should be encouraged to share their positive experiences with using any innovations, in order to create a positive influence on others.

7.4 Mediations

Using two different approaches (Baron and Kenny & Bootstrapping), mediation effects were tested in the post-hoc model. The results suggest that some relationships in the model are mediated by three constructs: V, PE, and TandFC. Existence of mediation effects indicate that some of the variance of the DV is explained by the mediator and not only by the IV. This section briefly discusses three significant mediating effects found.

7.4.1 Mediator: Visibility (V)

Visibility of the innovation acted as a mediator on two relationships in the model: **SI_IMG V TandFC** (full mediation) and **PE V TandFC** (full mediation). Both of these relationships are fully mediated by V. This indicates that much of the variance in TandFC in these relationships is being explained by V. Earlier, it was noted that V and TandFC have a high correlation indicating that they are related.

7.4.2 Mediator: Performance Expectancy (PE)

Performance expectancy acts as a mediator on five different relationships in the model: **SI_IMG PE V** (partial mediation)**, SI_IMG PE BI** (partial mediation), **SRE PE BI** (partial mediation), **EE PE V** (full mediation), and **EE PE BI** (partial mediation). Some of these relationships are fully mediated while others are partially mediated. PE seems to be mediating many of the relationships in the model and explaining some of the variance in these relationships.

7.4.3 Mediator: TandFC

TandFC acts as a mediator in one relationship in the model: **V TandFC BI** (full mediation). The relationship is fully mediated by TandFC. This indicates that much of the variance in BI for this relationship is being explained by TandFC.

7.5 Summary

In this chapter, the aim was first to summarise and present key findings resulting from the study. These findings were then discussed in more detail with reference to previous studies where such support was found.

The detailed discussion started with the various constructs tested by both models (original and post-hoc). After that, moderation and mediation effects were also discussed.

Some results have no prior support in the literature and they are considered new findings contributing to the research field. These are worth additional attention and testing in the future.

Next, in the discussion chapter, we draw findings and prior research together while exploring the significant contributions made by this study. Then, we synthesize and present practical recommendations to help encourage the adoption of innovations that enhance learning within UK universities. Limitations and recommendations for future work are also presented at the end of the next chapter.

8 Discussion

UK Universities, nowadays, are facing a lot of issues and problems such as budget cuts, changing environments, and rapid developments. These and other challenges are also impacting members of staff at these universities. They are overburdened, pressured and sometimes falling behind with their marking and other duties.

There is a clear need for change in universities. Seymour (1993) summarises it very well: “We are kidding ourselves if we believe that educating people for the year 2000 is essentially the same as educating them for the year 1975. Everything has changed, technology, lifestyle and culture. Our educational institutions must change as well.” We are in 2014, yet still, the traditional methods of lecturing and educating students are widespread and being used in many universities.

Innovative methods and approaches in learning within UK and other universities do exist. However, the problem is that because they are new and not considered the norm, they tend to be confined and used by some individuals or teams within organisations.

Some of these innovations may actually be very good at improving the education provided to students especially when compared with decades-old teaching approaches. However, such innovations are hardly found, and if found, the innovation diffusion and studies in the field prove that diffusion of such innovations is a complex process that involves a number of conditions or criteria that need to be met for this to occur.

To understand better and facilitate the diffusion and use of innovations that enhance learning, there is a need to put ourselves in members of staff’s place and ask: **Why change?**

As pointed out earlier in chapter 1 and also reinforced throughout this study, there are far too many issues and pressures going on in the daily life of university staff. As a result, any initiatives that require any change in the routine or “status quo” must be accompanied by reasons that encourage the individual to accept and favour the change. This is not to say that all members of staff are against change. Rather, with the pressures they are facing, there have to be strong reasons encouraging members of staff to accept change. Otherwise, it is unlikely that such efforts would be widely accepted.

In addition to the above, the fact that tenure and academic promotion leads to tangible rewards which are usually tied to research activities threatens any other activities that are likely to require resources (e.g. time, money, effort). Consequently, members of staff may be discouraged to pursue activities which are not tied to rewards.

To encourage adoption of useful learning innovations, there is a strong need for universities to promote actively the experimentation with and the adoption of innovations. This includes looking after challenges or issues impacting staff performance or their ability to develop and test new approaches. Of course, not all staff members would be willing to directly test and try new and different approaches. However, for those willing to, all the support possible should be offered, from the top of the pyramid (i.e. top management) offering active support such as introducing supporting policy, resources allocation, and motivation systems, to the lower level supporting activities such as on-going technical help. Active and continuous support will in time encourage others to join in. As a result, the use of some effective and proven innovations can become the norm and others who are sceptical or slow in adopting may finally decide to join the pack.

On the other hand, if the top management did not accept this much needed change, if institutional support was absent, and issues and pressures on members of staff were not resolved or even escalated further, only those who Rogers (2003) classified as “innovators” may actually bother trying something new if their conditions allow (i.e. how much pressure is on them), not because there is reward in it but because they like to try new things. Of course, when this happens, there is very little chance for diffusion to happen. Therefore, it is not unusual to spot sometimes some members of staff who are using some amazing innovative techniques or approaches that enhance learning and then wondering why no one else is doing this. Such cases are usually confined to what could be called pockets of excellence or innovation, where the results are much better than when using traditional approaches. Yet, because of the lack of active support, among other reasons driving diffusion, no one else knows or is encouraged to try.

When individual reasons for resistance or rejection (e.g. fear of change or fear of the unknown) of an innovation are coupled with institutional barriers (e.g. lack of active support, free time, and associated rewards), we could quickly get a better idea of why the adoption of innovations in universities have been very slow (Miller et al., 2000).

This research set out to investigate what leads to the adoption of innovations that influence learning within UK universities. It was hoped that through such understanding, more and more universities could encourage members of staff to adopt and use new innovative approaches, technologies, or methods that help improve learning for students.

Embarking on this journey, the novelty of this study consists of:

1. Extending and modifying the UTAUT model to investigate the adoption of learning innovations within UK universities.
2. Being the first to investigate the adoption of different multiple learning innovations across different UK universities.
3. Adopting, and where needed, developing or proposing measures that were used to capture relevant information.
4. Investigating and uncovering some interesting relationships.
5. Investigating moderation and mediation effects and uncovering findings that were not reported before.

In this chapter, the research discusses how the research questions and objectives were achieved. Moreover, this study contributed significantly to the literature. These contributions in addition to practical implications are also discussed in details below.

8.1 Answering the Research Questions

This study sought to answer two research questions. These are:

I. How well would a modified UTAUT model explain the adoption of learning innovations within UK universities?

II. Would students' requirements and expectations and students' learning influence the adoption of learning innovations within UK universities?

In order to answer these research questions, the following objectives were formulated:

1. Identify current areas where the UTAUT model is being tested.
2. Investigate other constructs that may help explain the adoption behaviour.
3. Propose and define any additional constructs that may help explain the adoption of learning innovations within UK universities.
4. Define the main hypotheses to be tested.
5. Develop the appropriate research methodology to collect the data.
6. Develop or adapt measures required to test the proposed adoption model.
7. Collect empirical data to test hypotheses and investigate relationships.
8. Test the defined hypotheses.
9. Investigate moderations and mediations to better understand how they may affect the adoption behaviour within UK universities.
10. Based on the literature and the findings of this study, present practical information that can help in encouraging the adoption of learning innovations within UK universities.

To fulfil these research objectives and to contribute to answering the research questions, the researcher **discusses each objective below** while referring to where it was tackled within this study.

- **Objective No. 1**

  To answer the first research question, the researcher started by investigating areas where the UTAUT was validated in the literature. Of particular interest was finding out whether the UTAUT was used in educational contexts and if such applications were of the model itself or an extended or modified application. Similar to TAM and previous models, applications of the UTAUT were mostly done using students, not staff members. No educational-related constructs were tested, indicating a possible gap for the researcher to fill.

- **Objective No. 2**

  While investigating the literature, another goal was to identify other constructs that may help explain the adoption of learning innovations within UK universities. A number of such constructs were identified (outlined in section 3.1.2 earlier). These were not considered in the UTAUT but they were worthy of further investigation in the context of this study.

- **Objective No. 3**

  To answer the second research question and as a result of not being able to find educational-related constructs that may explain the adoption of learning innovations in UK universities, to tackle this gap, the researcher decided to propose two new educational constructs that are logically sound. These were discussed earlier (section 3.1.3).

- **Objective No. 4**

  Once the above three objectives were accomplished, the researcher then formulated a number of hypotheses to be tested. Some inconsistencies in the literature were identified as part of the model development process, and these in particular were worthy of further testing, in addition to the other well-established relationships reported in the literature. For additional information, readers are kindly referred to the model development part of this study, where hypotheses were postulated (see chapter 3).

- **Objective No. 5**

  Once the appropriate hypotheses were formulated, it was then time to define the appropriate research design that would allow for collecting of the empirical evidence required for hypotheses testing. Consistent with previous studies, the study adopted a quantitative research design. For additional information, readers are kindly referred to the research approach section (section 4.2).

- **Objective No. 6**

  In order to collect accurate information, the researcher adapted and modified existing well-established measures to suit the needs of this study. Additionally, some measures had to be developed by the author to capture information related to constructs proposed by the researcher which had no established measures. Readers are kindly referred to section 4.5, which discussed the instrument development and measured used. The reliability and validity of these measures and the measurement model were also assessed later (sections 5.6.2 and 5.7.3).

- **Objective No. 7**

  Once the data collection instrument was developed, the researcher ran a pilot-study on a small sample of academic staff members. The pilot study (section 4.7.2) provided excellent feedback which was taken into consideration in the main data collection phase. In the main data collection phase, data was collection from academic staff members. Initial results and the data screening procedure followed to prepare the data are discusses in chapter 5. Additionally, exploratory and confirmatory factor analyses were carried out by the researcher to understand and assess the underlying structure and the reliability and validity of the measurement model. For additional information, readers are kindly referred to sections 5.6 and 5.7.

- **Objective No. 8**

  Based on the results of the exploratory and confirmatory analyses carried out by the researcher, a structural model was developed. Goodness-of-fit (GOF) indices indicated that the proposed model fits the data well. Once GOF of the model was established, the researcher moved then to investigate the various paths, allowing for testing of the postulated hypotheses. Readers are kindly referred to section 6.1 which discussed the original proposed model.

  Moreover, based on some previous literature and indications from the SEM software used (SPSS AMOS), the researcher continued on an exploratory mode, trying to uncover and test additional relationships. This resulted in a much better model that fits the data much better than the first model did. For additional information, readers are kindly referred to section 6.2.

- **Objective No. 9**

  The use of SEM software allows researchers to investigate mediation and moderation effects. The researcher investigated such effects in both of the models developed and tested by this study. Results of these tests uncovered some interesting relationships, some of which were not reported in the literature before and certainly contribute to the body of knowledge. For additional information, readers are kindly referred to sections 6.1.3 (Original Model), and 6.2.7 & 6.2.8 (Post-Hoc Model).

- **Objective No. 10**

  Finally, to provide a rich picture for those aiming to encourage the adoption of learning innovations within UK universities, based on the literature review and the results obtained from this study, the researcher discussed a number of practical implications in much detail. These are presented later in this chapter (section 8.3).

8.2 Contributions to Knowledge

This study contributed significantly to the innovation adoption field. This section discusses the main contributions in detail.

8.2.1 Learning-related Measures

Measures developed for capturing information usually go through a robust process where questions are phrased and tested to ensure best results (see, for example, the process followed by Moore & Benbasat 1991). In this study, while most of the measures were adopted from existing studies, the author found no learning-related measures concerned with students' learning and requirements and how they might influence the adoption of innovations.

There was a need to develop and test measures that would help explain students' learning and requirements might influence adoption. The author took into consideration how similar adoption measures were phrased and attempted to develop measures that capture information for both constructs: Students' Requirements and Expectations Students' Learning.

Upon testing the reliability and validity of those developed measures, they appeared to be reliable and valid. Therefore, future studies may wish to make use of these measures or develop them further.

More importantly, these measures yielded useful information and they helped in understanding adoption within the education context. To be specific, the Students' Requirements and Expectations construct was found to influence both behavioural intention and use directly and indirectly. Such influences were also found to be moderated by work experience and the number of teaching hours. These are new findings that were not reported previously in the adoption literature.

8.2.2 Multiple Innovations, Locations (Countries), and Organisations

This study attempted to aggregate, analyse, and report information across different innovations, locations, and even languages. Pooling such data across different innovations/technologies or organisations is consistent with previous research in the field (e.g. Compeau & Higgins, 1995; Nistor et al., 2010; Venkatesh & Davis, 1996).

However, to do so, well-established measures had to be re-worded and re-tested. Additionally, other constructs suggested in the literature were included in this study's proposed theoretical model in the hope that a better understanding of innovation adoption within UK universities is reached.

Reliability and validity tests of the measures proved that measures used by this study are reliable and valid.

While pooling empirical data across different contexts is not new, aggregating and using information related to multiple innovations at the same time has not been done in relation to adoption of innovation within the higher education sector. Existing studies in the literature either use a single organisation or a single innovation (or technology) when studying adoption.

8.2.3 Extending the UTAUT

The UTAUT is an integrated model that explained a high percentage of variance in the adoption of technologies. However, the UTAUT was not developed within an education context and a number of issues related to the education context were not considered. There are no previous studies that attempted to extend, modify, and validate such adoption model within the UK and certainly not within UK universities.

As is the case with many other studies trying to push the boundaries within different fields, this study attempted to use a modified and extended version of the UTAUT to explain the adoption of innovations that enhance learning within UK universities. From a theoretical perspective, this research extends the UTAUT theoretical validity and empirical applicability, while also extending its the area of use by examining it within the context of UK universities to understand factors influencing staff members' adoption of innovations.

Investigation of the various relationships drawn and tested within this study uncovered some interesting relationships which were not previously reported in the literature. One such relationship was that visibility and facilitating conditions have a very strong correlation between them, indicating that they are related and might be reflecting a construct that incorporates them.

Another interesting and strong relationship that was found was Students' Requirements and Expectations (SRE) and its significant influence on the Performance Expectancy (PE) construct. This study is the first to uncover such a finding. Consequently, researchers seeking to understand innovation adoption within an education context should certainly include and test such a relationship and the direct and indirect influence of SRE on adoption.

Moreover, this study looked at moderating factors and included work experience as a moderating factor. Previous studies in the literature are mostly interested in the experience with using a particular or similar innovation or technology rather than work experience. This study showed that work experience moderated some relationships. For instance, it was found that those with more work experience give more weight and importance to their students' requirements and expectations when they are thinking about adopting an innovation. Work experience also moderated other relationships in the model. Consequently, work experience should be included as a moderating variable in studies investigating the adoption of innovation.

8.2.4 The Customer Perspective

One key theoretical contribution made by this study is the focus on and attention given to the customer perspective, and more specifically, how being aware of the customer may influence the adoption of innovations. Innovations (including technology, tools, and methods) usually have an impact that extends beyond the adopting user as their adoption and use of certain innovations may influence others (Rogers, 2003). For instance, within the context of this study, innovations used in the classroom by staff members are likely to influence students. Similarly, innovations that may be used to enhance the staff member's productivity may influence others within the department as well.

To date, most of the attention in the adoption theories and models has been on the adopter himself. However, of equal importance is understanding how being aware of the customer perspective may also influence adoption and to what degree. This study investigated two customer-related constructs and found one of these constructs, Students' requirements and expectations, to influence adoption.

8.2.5 Creating a Base Model for Innovation Adoption in Education

More important than extending and modifying an existing model, the main goal of this study was to pave the way towards understanding innovation adoption in universities. Previous models and theories of adoption were mostly developed and tested outside the education context. Even if they were tested within an education context, they did not include or look at factors specific to this context. For instance, a TAM or UTAUT would be applied and tested within an education context without attempting to research, propose, and test new factors that may be specific to context. In such cases, the theories used by the researchers are tested as is or with minor modifications.

This study aimed to test existing and widely reported relationships, but, at the same time, it was important to look at other potential factors that may be influencing adoption within UK universities. By so doing, future studies may benefit from what has been found or achieved in this study. For instance, future researchers may choose to develop new measures that are more accurate than existing measures. Others may choose not to include constructs that have a weak influence on adoption in this study, to focus more on other constructs that give better or more accurate results.

This study tested two models. The first was originally proposed based on the literature review. It is similar to the UTAUT, but, incorporates other constructs.

Also, to be able to study multiple innovations, previously established measures were adapted and some new measures were also developed. Based on the empirical data collected and the analysis (i.e. SEM), this model explained 29% of the variance in behavioural intention (BI). Furthermore, when testing for multi-group moderation, the model was able to explain up to 40% of the variance in BI for those respondents who have between 5 and 9 years of work experience.

The second model tested, the Post-hoc model, was reached by following some evidence in the literature and indications of possible relationships between the various constructs as shown by AMOS, the software that was used to analyse the data. Some SEM software packages provide useful information to researchers and can suggest relationships. Relationships that were logically sound or had some literature support were drawn and then tested. The final post-hoc model explained up to 30% of the variance in BI. Furthermore, when testing for multi-group moderation, the model was able to explain up to 39% of the variance in BI for respondents in two different groups: those who have between 5 and 9 years of work experience as well as when testing for male respondents only.

Being able to explain 30% and up to 40% of the variation is considered a breakthrough. These models certainly explained much of the variance considering that: the models tested multiple innovations, respondents were from different organisations, and some measures were not previously tested. In fact, the researcher was concerned that all of these reasons combined would lead to a very low explaining power. However, to the researcher’s surprise, the explained variance, although not as high as the 70% variance explained in UTAUT, is considered a very good start towards a better understanding of innovation adoption in universities.

8.2.6 Interesting & New Moderating Influences

Although there are many theories or models predicting innovation (e.g. technology) adoption and use, testing and understanding moderating influences is also key to understanding the whole picture (Venkatesh et al., 2003). Certainly within an educational context, or to be more specific, within the UK universities context, there is a clear need to understand what moderating influences exist and to what extent they influence adoption and use. This study investigated a number of moderating factors and uncovered some interesting influences some of which were not reported in the literature before. For example, gender was found to moderate the ReInv —> BI relationships proposed and tested by this study.

Moreover, using country as a moderating variable yielded interesting results for five different relationships. The influence of these relationships differed across countries.

Many other findings were uncovered when age, work experience, voluntariness, and teaching hours were also used as moderating factors. These were reported in sections 6.1.3 and 6.2.7. Significant moderations were also discussed in the previous chapter.

It is likely that future research will be able to uncover additional interesting influences especially if further moderating or independent (i.e. predictor) variables were tested within this or similar contexts.

8.2.7 Moderators and their use in other studies

In addition to investigating moderators and reporting new findings as discussed above, the findings can be of use by researchers in a wider area of research because most of the moderators that were looked at are probably in effect in many other contexts. For instance, age, gender, work experience, and education are all factors that are likely to be important in other contexts. Therefore, findings reported by this study that are related to these moderating variables can be of use to other researchers.

8.2.8 Interesting & New Mediation influences

In the post-hoc model, this study investigated the mediation effects of Visibility (V), Performance expectancy (PE), and Facilitation conditions (TandFC) as dependent variables.

First, the study found that V fully mediated the influences of SI_IMG and PE on TandFC. A high correlation between V and TandFC was also found, although there were no cross loading issues between these constructs during the EFA and CFA stages of this study. Additionally, no high modification indices where found during the structural model. Such modification indices would normally be high or very high if there were cross loadings. The researcher did not find any literature support that may help explain this finding. Additionally, TandFC was found to be fully mediating the influence of V on BI. Therefore, the V —> BI path dropped out of significance, and it was removed from the post-hoc model.

Trying to explain the complex relationship above might be difficult. However, one pleasing explanation is that perhaps V and TandFC can together form a single more general or higher level construct that encompasses both. This is not to say that they are measuring the same thing. Instead, they may be contributing to a higher level construct that could incorporate them. The current correlation and mediation may indicate that the perception of facilitating conditions is strongly tied to the perception of how visible the innovation is.

Second, another construct found to be mediating four of the relationships in the post-hoc model is PE. Three out of the four were partial mediations, while the fourth was a full mediation. These are new findings since the constructs involved were usually not looked at in previous studies. Therefore, these findings reveal the extent to which PE could influence adoption through mediation effects. The mediating effects by PE found were: **SI_IMG PE V** (partial mediation)**, SI_IMG PE BI** (partial mediation), **SRE PE BI** (partial mediation), and **EE PE V** (full mediation).

8.2.9 Further Support to Established Constructs

This study confirmed the influence of a number of constructs on intention or use. While some of the influences investigated may have been tested in different contexts, these were unlikely to have been tested in the same way before: across various innovations, locations, and organisations within the education context.

In particular, this study confirmed the strong influence of performance expectancy and found that it has various influences on other relationships. Such mediating influence was not found in the literature. Additionally, the influence from effort expectancy on performance expectancy was confirmed in this study. This is also the case with the reported influence caused by the social influence construct on behavioural intention. Additionally, social influence was found to also influence the performance expectancy and visibility constructs. These influences were not found in the literature as well.

The above influences found expand on the literature and offer new insights that help in the understanding of adoption.

8.2.10 Encouraging Adoption of Innovations within UK Universities

Studying the various factors influencing the adoption of innovations within the context of this study has showed which are influential and which are not. Moreover, studying mediating and moderating effects yielded some interesting results that should be explored further.

Therefore, this study contributed to the adoption literature by providing useful insights into what factors may affect adoption within universities.

Universities, departments, or other entities wishing to encourage adoption could certainly benefit from the findings of this study. However, the researcher cautions against taking these results as solid facts since more research is needed to understand further the influences caused by these or other factors on the adoption of innovations within universities.

8.2.11 Robust assessment and reporting of data

Despite the increasing attention given to innovation and technology adoption and the various studies being published, many of which are validating existing similar models, not much attention is given to the assessment of data to demonstrate robustness. For instance, many studies do not follow the good practices of reporting data in general or the reporting of SEM information as to help others in assessing the study and its results (Schumacker & Lomax, 2010).

Examples of this include: not reporting correlations, not reporting results of the assessment of multi-variate assumptions (if any to ensure they are not violated), not assessing and reporting the possible influence of common method variance, and more. Without assessing and reporting such influences, readers and researchers cannot be fully confident in the results, especially since, as demonstrated in this study, simply reporting the adequate validity and reliability of measures is not enough as there are many other influences to examine too. Consequently, researchers and those interested in this area of research would not benefit from simply readying results. It is very important to report or at least demonstrate awareness of these influences, what they are, and how such influence, if any, was kept to a minimum or at least clearly reported.

This is perhaps not a direct contribution to the field itself but rather the aspiration to assess and report data clearly and accurately to be of more use to future researchers, and at the same time, hopefully, to encourage future researchers to give more attention to the assessment and reporting of such diagnostic data.

8.3 Practical Implications

From a practical perspective, this research contributes to a better understanding of innovation adoption within UK universities and how adoption can be encouraged.

Many of the recommendations presented here are interrelated and highly dependent upon one another in some cases. However, more importantly, they are also dependent on the degree to which issues and pressures discussed earlier (see 1.1 Issues Facing UK Universities) are resolved, or, at least, their negative impact is mitigated. Therefore, there will be some repetition in what is going to be discussed next, while continuously referring to the challenges facing UK universities and their impact on staff. Such repetition occurs only because many of the issues facing UK universities are in conflict, overlapping, causing more issues, or possibly influencing the adopting of innovations.

The following practical implications were derived in part from the various findings of this study. Also, they were derived, to a notable extent, from the many studies discussed in this work. These practical implications are important to anyone seeking to understand or encourage innovation adoption within UK universities in particular. However, they could be of help to other universities as well and possibly within other educational institutions.

8.3.1 Customer Perspective: Implications for Researchers using Factor Models

As demonstrated in this study, when applicable, attention can and should be given to the customer (in this study students) perspective. Researchers investigating the adoption of innovations or technologies should consider adding and capturing information related to the customer perspective, if the intention to adopt the innovation in question could be influenced in such way.

In this study, it was expected that students-related factors would have some influence on staff members' decision to adopt innovations. In other cases or studies, it may be that the user who is considering adopting an innovation has a similar influence. For instance, a company deciding to adopt and use an online software solution to manage and send invoices to customers automatically should be aware that their choice is likely to have an impact on their customers. In this case, employees who are considering using such software should ideally be influenced by what their customers would say.

Lastly, by capturing and giving more attention to the customer perspective (when applicable), we may be able to improve the predictive power of some models as this may explain some of the variance in the intention or use of innovations. Hence, more research should be given to this area.

8.3.2 Managerial and Institutional Support and Resources

Top management's active involvement is important to drive and encourage innovation within organisations (Brands & Kleinman, 2010; Dyer et al., 2011). Wastell and Cooper's (1996) study comparing two similar innovations in the service sector alerts us to the magnitude of the failure and potential impact on lives resulting from the lack of proper top management support.

The availability of institutional support is thought of as an enabler that could influence staff members' decision to adopt or reject innovations. Hazen et al. (2012) found that management support was one of the most important factors influencing educational innovations adoption and dissemination. Spodark (2003) also argues that without the institutional vision and pro-active leadership, it is unlikely that much diffusion would occur.

Tabata and Johnsrud (2008) in their study found a negative association between institutional support and the availability of resources and the likelihood of participating in distance education. They suggested that this may have been as a result of members of staff not being able to access the resources that were available as a result of being busy or resources being not easily accessible.

In contrast, Moser (2007) in his research strongly endorses organisational support by providing incentives and activities that help members of staff in their adoption and in competence development activities. Put simply, organisational systems and policies need to support and encourage staff members to develop innovations or technologies and to be involved in any competence development or other activities that may spread awareness about various innovations and how they can be used. In the absence of such clear and active institutional support, it is unlikely that diffusion would take place and members of staff would be less likely to sustain their efforts (Nachmias & Ram, 2009). Even if diffusion of some innovations takes place, significant improvements to education would be unlikely to happen (Soffer et al., 2010).

8.3.3 Time

Time was an obstacle identified by a number of studies investigating the adoption and use of different technologies or innovations (Bingimlas, 2009; Franklin, Turner, Kariuki, & Duran, 2001; Jacobsen, 1998; Nachmias & Ram, 2009; Peluchette & Rust, 2005; Tabata & Johnsrud, 2008). Being innovative does not just happen, it requires a significant time investment (Dyer et al., 2011).

As mentioned before, many members of the sample who were contacted were unable to participate as a result of time constraints. Agreeing with Moser (2007), time is indeed a “scarce resource” and staff members have many tasks taking up most of their time. Therefore, the lack of release time would likely influence the adoption of technologies and innovations negatively, especially if the adoption and use of such technologies and innovations requires an initial or on-going time investment from staff.

The author agrees with Tabata and Johnsrud (2008) with regard to the importance of the coexistence of the use of technology or innovation and other duties assigned to members of staff such as teaching, research, service, and administrative work. If universities were to create such coexistence, members of staff could then have dedicated time to test and adopt technologies and innovations some of which may help in achieving more benefits and improvement. Additionally, the author agrees with Moser’s (2007) discussion of time commitment and its relation to competence development and the engagement in various activities related to the innovation or technology in question.

Keeping in mind that members of staff are pressured, the use of some innovations may help save time associated with instruction, interaction, or other teaching-related activities (Kulik & Kulik, 1987; Lonn & Teasley, 2009). However, the fact still remains that an initial time investment would still be required.

8.3.4 Education and Training

Rogers (2003) discussed the importance of training and helping individuals in overcoming any fears or uncertainties related to the adoption and use of the technology or innovation in-question. Jacobsen (1998) reported that lack of training was a barrier to widespread use of computers. Similarly, Bingimlas (2009) argued that lack of effective training was one of the most frequently mentioned barriers to adoption of ICT.

Tabata and Johnsrud (2008) associated the willingness to adopt and use technologies or innovations to individuals' perception of adequate training. Their results also suggested that having the necessary skill to use the technology or innovation is important. However, such skill would be developed after adopting and using the innovation or technology in question in the first place. Therefore, they recommended encouraging faculty to interact with a technology or innovation (in their case distance education) that requires minimal training and development efforts.

Many researchers stressed the importance of competence development activities (e.g. training) for successful adoption or diffusion (Bingimlas, 2009; Birch & Sankey, 2008; Jacobsen, 1998; Miller et al., 2000; Moser, 2007; Roberts et al., 2007; Wastell & Cooper, 1996). Such activities could educate and develop staff members to help reduce some uncertainties (Franklin et al., 2001; Miller et al., 2000; Rogers, 2003) and to overcome lack of confidence issues (Bingimlas, 2009). Therefore, these activities could lead to a more favourable decision with regard to adoption.

Furthermore, since the perception of the complexity of the innovation can influence its adoption (Hazen et al., 2012; Rogers, 2003), competence development activities may also be used to help familiarise individuals with various innovations and their benefits.

Based on the above, education, training, mentoring or competence development activities in general could help members of staff to become more competent in using innovations as well as aware of what sort of positive impact they may have on students learning (Roberts et al., 2007). Such activities may also help to educate or guide members of staff towards understanding the diversity of learning styles and how and which methods or innovative approaches are best used and when. For instance, Nachmias and Ram (2009) reported that while there were some innovative ideas by some instructors utilising the Web, other instructors were not as innovative and simply posted plain content (e.g. text based) for students to read. Plain content material may be useful in certain situations but building interactivity into the content is certainly important.

Lastly, because age, work experience, gender differences, and the number of teaching hours all played a moderating role on some of the relationships explored in this study, universities may wish to design their competence development activities to cater for the various needs or concerns of these different groups.

For example, younger members of staff were found to give more weight to their students' requirements and expectations. Therefore, competence development activities could explain how certain innovations could help meet or exceed these requirements.

8.3.5 Usefulness of the Innovation

The usefulness of the innovation is a construct that has received much attention and gained much support as one of the strongest predictors of the intention to use an innovation (Chau & Hu, 2002; El-Gayar & Moran, 2006; Jong & Wang, 2009; Lakhal et al., 2013; Lee et al., 2005; Liu et al., 2005; Martins & Kellermanns, 2004; Oye et al., 2012b; Selim, 2003; Venkatesh & Davis, 2000; Yamin & Lee, 2010).

Consistent with previous studies in the adoption field, performance expectancy or usefulness of an innovation was found to be a strong influencing factor on whether or not members of staff would adopt and use an innovation. Consequently, the advantages or benefits of using an innovation should be made clear for others to see or experience first-hand. Otherwise, potential adopters may be reluctant to adopt, thinking that the innovation in question may make their job harder (Wastell & Cooper, 1996).

Within universities, advantages or benefits may be, for example: reduced teaching time, a more efficient way for contacting students, easier and less time consuming way to mark, and so on.

Performance expectancy was not only influencing the intention to adopt innovations directly, in this study, it was also found mediating a number of relationships. Therefore, this is a critical component of the adoption process and it should not be left out of any competence building activities or any awareness or other efforts aiming to encourage adoption within universities.

Referring back to the pressures and issues facing members of staff within UK universities discussed in the first chapter, it is not difficult to see why benefits and advantages should be clearly communicated. Otherwise, members of staff are likely to lose interest in such initiatives some of which may be of benefit but were not communicated or presented to them properly.

8.3.6 Ease of Use of the Innovation

There are some inconsistencies with regard to the influences of effort expectancy (EE). Some studies did not find any influence on behavioural intention (BI) (Jong & Wang, 2009; Park, 2009; Sumak et al., 2010; Venkatesh et al., 2003) while others did (Boontarig et al., 2012; El-Gayar & Moran, 2006; Martins & Kellermanns, 2004; Oye et al., 2012b; Yamin & Lee, 2010). In this study, the researcher tested for the influence of EE on BI. Results were in line with the first group of studies as EE's influence on BI was insignificant.

Moreover, TAM posited that perceived ease of use (PEOU) was a significant predictor of perceived usefulness (PU). Many studies confirmed this (Lin & Lu, 2000; Martins & Kellermanns, 2004; Saadé et al., 2007; Sun & Zhang, 2006). In line with these studies, EE was found to be a strong and significant predictor of PE ($b^* = 0.243$, $p < 0.001$).

Within universities, the ease of use of the innovation should be stressed. Staff members who are already overburdened are less likely to adopt and use innovations that are very difficult or require big investments (e.g. time and resources). In particular, potential adopters should be fully aware of what is required of them and the level of complexity or difficulty associated with using an innovation. Keeping in mind that the higher the complexity, the less likely adoption will happen (Rogers, 2003), competence development or awareness activities should stress the ease of using the innovation in question. Perceiving the innovation as being easy to use could in turn influence the perception of its usefulness, possibly leading to a more favourable decision regarding the adoption.

8.3.7 Communicating Successes & Learning from Failures

The diffusion process is a social process which relies upon interpersonal communications as individuals usually give much weight to the subjective evaluations of others (Rogers, 2003). Roberts et al. (2007) recommended encouraging a few influential members of staff to adopt and use innovations in the hope that they will influence others.

One important point to keep in mind is that members of staff are likely to vary with regard to their personal characteristics within universities and it is unlikely that all staff are homophilous (i.e. have similar attributes such as beliefs, education, status, etc.) (Rogers, 2003). However, as Rogers explains, the interpersonal communication of ideas usually happens between individuals who are homophilous. Therefore, in order to encourage diffusion of innovations between individuals, it is best to target and encourage different influential staff that may have similar characteristics to different groups within the university.

Roberts et al. (2007) recommends faculty sharing of experiences. In contrast, Tabata and Johnsrud's (2008) study suggests that sharing of experiences may be counterproductive especially in the case of bad experiences which may dissuade others from trying. Sharing bad experiences is mostly unwelcome in organisations where culture does not encourage risk taking and learning from failures. In the context of this study, universities are certainly not known for their innovativeness, creativity, and risk taking. Still, however, with the right amount of encouragement, support, and mind-set change, the culture could certainly be changed to embrace and learn from failures. However, this is outside the scope of this study and is likely to be a difficult and long process.

8.3.8 Visibility of the Innovation

Rogers (2003) and Wejnert (2002) argued that the visibility of the innovation and its impact could lead to more adoption as potential adopters become more familiar with the innovation and less worried about the risk associated with adopting it.

This study tested the influence of visibility (V) on behavioural intention (BI) and found it to be insignificant. However, in the post-hoc model, it was found that V had a significant influence on facilitating conditions (TandFC). Furthermore, TandFC was found to be fully mediating the influence of V on BI. This explains why the V —> BI path was insignificant in the post-hoc model.

The influence of V on TandFC found above could indicate that potential adopters at some stage may be interested in finding out whether others are using the innovation in question and whether they were successful in doing so. Therefore, to encourage adoption within universities, successes and positive results associated with the use of a certain innovation should be communicated.

8.3.9 Facilitating Conditions

There are some inconsistencies with regard to the influences of facilitating conditions (TandFC). Some studies found that it influences actual use (Oye et al., 2012a; Sumak et al., 2010; Venkatesh et al., 2003) while others found it to influence significantly the behavioural intention (BI) to use an innovation (Jong & Wang, 2009; Lakhal et al., 2013). Consistent with both groups of studies, it was found that TandFC significantly influences BI and Use, although the influence on BI is weak.

New innovations and technologies are being introduced into our lives and those of our students at a very fast pace. While some of these innovations and technologies may be used to enhance learning, it is expected that not all members of staff would be aware of how to use them effectively. Therefore, technical support is critical especially nowadays as a result of the widespread use of information and communication technologies.

Moreover, some studies (Franklin et al., 2001; e.g. Jacobsen, 1998) reported that lack of technical support was a big obstacle hindering the use and spread of technologies in education. Franklin et al. (2001) reported a study where a mentoring approach was used to help teachers understand and use technology more rapidly. Teachers in the study appreciated that mentors were available and offered support directly when needed, which helped them in developing and improving what they offered to their students.

Within universities, supporting conditions should be in place to support the use of innovations. Such supporting conditions may include: training, mentoring, easy access to the technical support team, getting help quickly when needed, maintenance activities, and providing any devices or software needed. Universities wishing to encourage the adoption of innovations should at least understand and make available the necessary facilitating and supporting conditions to increase the odds of it being adopted and used.

8.3.10 Motivation and Compensation

Rewarding the adoption and use of technologies, innovations or good teaching approaches is key to encouraging adoption and use (Rogers, 2003; Smith, 2012; Spodark, 2003; Tabata & Johnsrud, 2008). However, is such encouragement taking place within UK universities today?

The literature suggests the lack of proper incentives or reward systems for educational technology adoptions and use (Roberts et al., 2007). Based on what could be referred to as the norms in universities, it is unlikely that certain systems are put in place to encourage the use of innovations that could enhance learning. Excellence in teaching has yet to reach a level where it can be compared with excellence in research (Modernization of Higher Education Group, 2013), although encouragingly, some attention is going into that direction.

The fact that tenure and academic promotion are strongly tied to research-related output is likely to demotivate some staff from improving what they are doing. A recent official report published by the EU's High Level Group on the Modernisation of Higher Education acknowledged the fact that not enough emphasis is placed on teaching (Modernization of Higher Education Group, 2013). It also calls for the need to dedicate the necessary human and financial resources, link staff promotion to teaching performance, and to integrate the need for quality and improved teaching in universities' missions. How much resources would be actually dedicated to this goal is perhaps something the EU commission or at least individual countries should continuously measure and act-on. Otherwise, such much needed change may never happen.

To encourage members of staff to experiment with various innovations or technologies, universities must put in place a reward structure that motivates staff (Miller et al., 2000; Nachmias & Ram, 2009). Otherwise, with the current reward structure used at most universities, staff members who hardly have any spare time would certainly be reluctant to adopt new approaches or tools that would be likely to require some of their time.

8.3.11 Voluntariness or Mandatory adoption

Being pressured to perform various tasks probably means that staff members would rather not adopt innovation or technology that is likely to require some initial or on-going investment. Therefore, if the use of such technology or innovation is voluntary, why should they bother themselves by adding more workload? Similarly, many students reported that because use was voluntary, they did not want to commit to tasks that may require more of their time as they are quite busy (Jonas & Norman, 2011).

Moreover, findings suggest that those less likely to participate in distance education are more likely to think of such participation as being voluntary (Tabata & Johnsrud, 2008). Similarly, Venkatesh and Davis (2000) found that individuals would use a system more frequently if they perceived the use as a requirement. They call this a “compliance-based effect”. Jonas and Norman (2011) also found a negative relationship between voluntariness and use.

Based on the above, it can be seen that unless the adoption of a certain innovation is mandatory, it is unlikely that many would adopt it, especially if they are already pressured with performing too many tasks and have little time to spare. However, unless these key issues (e.g. lack of time, rewards, etc.) hindering active and effective adoption and use are tackled, it is unlikely that the use of such mandated innovations would be as desired. This means that such innovations might be used by staff because they were asked to do so, yet, they may not give it much thought, it may not be used effectively, or in the worst case scenario, it might be adopted for some time and dropped later as a fad.

The author believes that having to mandate the use of an innovation might not be a good choice as its full and effective use of it may never happen. On the other hand, if advantages and ease of use are demonstrated to members of staff, they are likely to consider using innovations which would help make their lives better. However, the issue here is that too many pressures facing staff have stripped them of the luxury of spare time and the desire or state of mind to pursue, test, and try new things. Consequently, they are more likely to perceive other things as more harmful.

8.3.12 Students' Requirements and Expectations

In this study, and as proposed and expected, students' requirements and expectations were found to be a significant predictor of behavioural intention to adopt innovations. Moreover, the perception of whether students' requirements and expectations will be achieved by adopting a certain innovation was found to have an influence on the performance expectancy construct as well. Therefore, staff members who perceive that an innovation will help them in meeting or exceeding students' requirements and expectations are more likely to perceive that the innovation is useful. Such perception of the usefulness will in turn influence the behavioural intention.

Roberts et al. (2007) in their study found that students' perceptions exerted some influence on the faculty decision to adopt classroom technologies.

Both teaching hours and work experience as moderators were found to influence the relationship between students' requirements and expectations and the intention to use an innovation. More specifically, results indicate that as they work more (work experience or teaching hours increases), staff members give more weight to how the innovation that is adopted or to be adopted will help them in meeting or exceeding their students' requirements and expectations. This may indicate that as they work more, staff members become increasingly knowledgeable of their students' requirements and expectations and the need to meet or exceed those expectations.

Within universities, when there are attempts to encourage adoption and use of some innovations, it should be clear how these innovations will help in meeting or exceeding students' requirements.

8.3.13 Modification, Alteration, or Reinvention of Innovations

The degree to which innovations are flexible and easy to adapt to suit adopters' needs is important. Innovations that are more easily adapted or modified are more likely to be adopted (Hazen et al., 2012; Rogers, 2003). The results obtained in this study also reinforce such conclusion. Therefore, individuals, departments, or universities as a whole wishing to encourage diffusion of innovations should help others understand the degree to which these innovations can or cannot be modified or adapted to suit their needs and contexts.

8.3.14 Sustainability and Spread of Innovations

The sustainability and diffusion of effective innovations that enhance learning (or any effective innovations) is highly important. Adopting useful innovations for a certain time and then dropping them for no reason is certainly a poor investment of time and resources especially if the adoption and use of such innovations requires an initial time or resources investment. Hence, it is important to understand what factors may influence the continued use of innovations.

Nachmias and Ram (2009) found that a major issue for their study of various innovations and technologies used in education was that innovative models were not sustained and diffused as a result of insufficiently rewarding members of staff.

Moreover, closely related to the previous recommendation above, the sustainability and spread of an innovation is also influenced to some degree by the ability to reinvent it (Rogers, 2003); innovations that are flexible are more likely to be useable in more contexts or for different uses by staff. Therefore, adoption is less likely to be discontinued as a result of the innovation fitting the context or circumstances (Rogers, 2003). For example, not only can personal computers be used to design and deliver curriculum, they can also be used to contact students and interact with them in many different formats (e.g. recorded video, live video, written, etc.).

Identification of the various issues facing members of staff within UK universities, the review of the literature, and the fact that many members of staff apologised for not participating due to lack of time are indeed concerning. Unless the aforementioned recommendations are tackled (i.e. the issues are resolved), it is unlikely that sustainable or effective widespread diffusion would occur. Instead, it is likely that the use of such innovations would continue to be confined to certain areas.

8.3.15 Diffusion within the UK HE Sector

It is not unusual to see excellent or innovative approaches and methods adopted by certain members of staff within some universities. However, since these do not represent the norm, they will not be easily adopted and diffused especially if there is no active support for such adopters and innovators within their institutions. Hence, although such innovations may be very beneficial, their positive impact is limited.

With increases in scholarships and the numbers of international students in recent years, there is a national need to improve and attract more students to secure greater funding. Within the UK, there are a number of respected universities which are likely to attract many students. However, from the HE sector perspective, would it not be better if many more universities were able to do the same? Would it not be better if the HE sector as a whole was improved to compete with or overcome HE systems in other countries? One approach that may help in reaching such a goal is the diffusion of innovative approaches or methods that have proven effective but which are confined to certain departments within certain universities.

Across the UK higher education sector, if there is desire to improve and diffuse innovative approaches within UK universities, there has to be a central effort (as suggested by Nachmias & Ram, 2009 and Modernization of Higher Education Group, 2013). Such an initiative, which needs the highest level of support possible, in addition to plenty of resources, could motivate fruitful discussions between innovators and early users of innovations and technologies that enhance learning. Through these discussions and the various projects and activities, existing methods could be improved and new approaches suggested and tested on a small scale. Additionally, success stories could be spread while failure cases could be assessed and lessons learned drawn.

Then, the diffusion of good and successful approaches across UK universities could take place, and with increased adoption of such innovations (with the right university and national support), these could become the norm, leading to further adoption by more members of staff who would be less afraid to adopt or simply not want to be left behind.

8.4 Limitations and Issues

As is the case with any research, there are some limitations and issues faced by this study which are briefly discussed in this section.

8.4.1 Sample Size, Response Rate and Generalisation

One of the main aims of this research was to benefit from a large sample, in order to better understand the diffusion of innovation within UK universities and be able to generalise findings. Therefore, the researcher sent out participation invitations to 17,754 staff members from 27 UK universities. However, a little over 500 responses in total were received. Although it may have been possible to send more follow-up messages, the decision was made not to do so, to avoid disturbing members of staff who are likely to be pressured and busy. A number of e-mails were received from people explaining why they could not participate. Almost all of these e-mails cited the lack of time or having too much work to do as main reasons for being unable to respond. This confirmed the fact that members of staff are over-burdened, as discussed in chapter one.

Moreover, there is the possibility of the inherent bias where only staff members who had the time or were motivated to respond did so. Whether or not they responded because they are innovators or understand and agree to the need for innovation diffusion is not clear. Therefore, there is the possibility that the data might be skewed as a result of this bias.

As a result of the very low response rate, one drawback is that it is not possible to generalise findings to the wider population of UK universities as findings might not be applicable everywhere. Still, however, rich and useful practical implications were formulated, based on the extensive literature research as well as findings from this study.

8.4.2 Self-reported Perceptions

The survey questionnaire adopted by this research relied on personal opinions and perceptions as reported by the participants. Hence, responses may not reflect accurately how respondents feel or believe. Therefore, findings and results reported by the study should be interpreted or used with caution.

8.4.3 Use of a Variety of data collection methods

Rather than rely fully on self-administered questionnaires, future research could consider using another data collection method or a combination of methods such as observations, actions research, and/or collecting data at different periods of time. Moreover, certain technologies may be used within the institution to track and report usage of certain tools. The use of different data collection methods could help in understanding whether the nature of the widely used questionnaire instrument is influencing or causing problems in researching and understanding the adoption behaviour. Moreover, other data collection methods may be more accurate especially with regard to capturing actual adoption and use of innovations and technologies.

8.5 Further Research

The following recommendations for future research are based on findings, shortcomings and limitations of this study, as well as areas worthy of additional investigation.

8.5.1 Response Rate and Generalisation

As explained above, despite the large sample drawn, the very low response rate does not allow for generalisation of the findings.

Future studies may benefit from testing the same model or an improved version of it using while thinking of other ways to improve the response rate. Otherwise, future studies will run into the same issue of having very low response rate.

One possible approach to improving the response rate is contacting and getting universities' permission to engage and contribute to the study. Such official approval may give more weight to the study, especially since staff members receive regularly, invitations to participate in similar student studies. Another similar approach would be to contact any EU or UK overseeing higher education groups, initiatives, or committees, to gain a similar official cover.

8.5.2 Students' Requirements and Students' Learning

Earlier in this study, the author postulated that students' requirements and expectations (SRE) and students' learning (SL) both have an influence on the adoption of innovations within universities. However, model testing showed only SRE as a significant predictor of innovation adoption. SL, on the other hand, was dropped for having no significant relationship to BI in the post-hoc model. While it is not unusual that such findings are the result of newly developed measures possibly in need of further development and testing, the author is concerned that this might not be the case. There is perhaps another possibility that raises concern which is worth investigating in the future.

Students' requirements and expectations are strongly tied to university guidelines and standards. Students who are not satisfied have proper channels to voice their concerns. On the other hand, students' learning is not easy to measure and the method of instruction or delivery is usually left to the lecturer. In the worst case scenario, the lecturer may use the same spoon-feeding method of instruction and no one would question that; because it has been the typical method of instruction for decades.

What is of concern to the researcher is that perhaps SRE was found to be a significant predictor of adoption because staff members placed more emphasis on complying with university rules and standards to keep those students coming. On the other hand, they may not care as much about providing the best learning experience possible to students because that is not required of them. Developing better methods that may lead to better learning requires some form of investment by staff members – time and possibly some research. However, as we know by now, staff members do not have such time available due to budget cuts and increase in workloads. Therefore, perhaps they do not go the extra mile to help their students to learn more because either: a) this is not required of them and/or b) they do not have enough time to do so.

8.5.3 Refinement of the measures

Measures used in this study have shown good validity and reliability and most of them were previously established and rigorously tested. New measures created by the researcher have also shown good validity and reliability. However, modifying these measures and trying to capture information related to multiple innovations rather than one specific innovation or technology may have caused some understanding issues or inconsistencies in answers. For instance, in this study, respondents who reported adopting a learning innovation were asked to answer the questionnaire based on their experience when first adopting this particular innovation. However, their answers may be influenced by a number of things: Do they remember when that happened? Could they be confusing this innovation with something else? Did they understand the question clearly?

Based on the above, it may be appropriate to go through a rigorous instrument development process where participants take rounds and help improve the instrument to ensure minimal impact and more accuracy when collecting data. It is possible that the variance explained by this model was also influenced to some degree by this issue.

8.5.4 Investigating other constructs

Although the model was able to explain 30-32% of the variance in behavioural intention, which is considered reasonable especially as a first step towards understanding the adoption of learning innovations in UK universities, it is recommended that researchers investigating adoption within this and similar new contexts conduct exploratory research that may help to uncover additional factors influencing individuals' adoption decisions. Interviews are likely to yield rich and in-depth knowledge of other possible factors, which could be useful as a first stage before the model development and testing stage.

Despite the fact that the UTAUT is a robust model integrating a number of adoption theories and models, it is likely that there are other constructs influencing adoption within an education, or, to be specific, higher education context. Uncovering such constructs will help in understanding the adoption of innovations within such contexts better.

8.6 Summary

In this chapter, the aim was to start by reminding the reader of the main research questions, research objectives, and how these were fulfilled. To answer the first question, the researcher modified and extended the UTAUT model, taking into account constructs investigated by other scholars in the literature. Moreover, two learning-related constructs were also proposed by the researcher to answer the second research question. This included the development of measures for these newly added constructs.

After that, significant contributions to knowledge made by this study were discussed.

Moreover, based on the results of this study and the investigation of the innovation adoption literature, practical implications were discussed in details. These are considered important for any and all individuals and universities wishing to encourage the adoption of innovations.

Limitations and issues faced by this study were also presented and recommendations for further research were discussed.

Next, to conclude, we briefly summarise key findings of this study and present a summary of the practical implications discussed earlier in this chapter.

9 Conclusion

UK universities are facing a number of challenges and in order to retain their positions as leading universities, there is a crucial need for improvements. The adoption of newer or better innovations or technologies can be considered one way to help improve current practices many of which remain rigid and outdated.

Moreover, technological advancements and the fact that today's generation is considered more comfortable with technologies, add more pressure on universities and educational institutions in general to improve and adopt new innovations. In short, students expect to continue to use new technologies in their university and while learning. Many such innovations and technologies also help students in searching, learning, making notes, studying, and more. Therefore, universities need to continuously think about how best to integrate the various innovations and technologies to enhance students' learning.

The adoption of innovations is a complex process. Not all innovations are adopted directly and the adoption rate differs. Therefore, understanding the reasons behind the adoption or rejection of technologies and innovations is important.

Rogers (2003), Davis (1989) and Venkatesh et al. (2003) established a good foundation for understanding the diffusion of innovations and what influences adopters' decisions to adopt or reject innovations or technologies. That being said, little attention has been given to the innovation or innovations within universities.

In particular, much attention should be given to innovation adoption in universities. After all, many researchers interested in innovation and technology adoption operate within various universities. It is only natural that they should give more attention to the adoption of innovations within their educational context, at some point if possible, to help develop our understanding of this particular area further.

This research was built on the aforementioned studies in order to reach a theoretical model that could help explain the adoption of learning innovations in UK universities. Members of staff from a number of UK universities were invited to participate in an online questionnaire which used already established measures to measure respondents' perceptions with regard to a number of constructs. Additionally, two new constructs were proposed and measures were created for these new constructs.

From a total of 17,754 members of staff invited, 499 completed responses were received from academic members of staff. SPSS and SPSS AMOS software packages were used to analyse the data. A number of analysis approaches were applied such as: Exploratory Factor Analysis, Confirmatory Factor Analysis, and Structural Equation Modeling.

This chapter begins by summarising the key findings and end with a summary of the practical recommendations to encourage adoption of innovations within UK universities.

9.1 Summary of Findings

In this section, the researcher briefly summarises some of the key findings of this study. To help the reader in navigating this thesis, we provide cross-references for the reader to follow in the following text. Additionally, the reader may benefit from the Thesis Outline (section 1.6)

9.1.1 The Development of Educational-related Constructs

Since previous models investigating adoption of innovation or technologies did not investigate education-related constructs which may possibly influence the adoption of learning innovations within UK universities, one of the main goals of this study was to propose two new constructs: Students' Requirements and expectations, and Students' Learning.

While investigating ways to capture information related to these constructs, no measures were found in the innovation adoption literature. Therefore, the researcher created new measures.

Measures related to both constructs developed and proposed by the researcher proved to be reliable and valid (see sections 5.6.2 and 5.7.3). However, only the students' requirements and expectations (SRE) construct was found to influence significantly **both** the behavioural intention and use. It was also found that SRE influences staff members' perception of the usefulness of the innovation.

By proposing these two new constructs and developing reliable valid measures to reflect them, future studies could benefit from using or building on such knowledge.

9.1.2 Hypotheses Testing, Behavioural Intention, and Use

Performance expectancy was found to be the strongest predictor of behavioural intention; this is consistent with previous studies (see sections 6.1 and 6.2.3). Effort expectancy, facilitating conditions, and reinvention were all found to also influence the behavioural intention significantly.

Moreover, with the use of logistic regression (see section 6.3), it was found that actual use of the innovation in this context was influenced by: behavioural intention, students' requirements and expectations, facilitating conditions, experience, and teaching hours.

9.1.3 Interesting Relationships

While exploring additional relationships in the post-hoc exploration stage, the researcher uncovered some interesting relationships some of which were not reported in the innovation adoption literature before.

Performance expectancy strongly influenced the visibility of the innovation. Moreover, consistent with some studies in the literature, effort expectancy was found to influence the performance expectancy of the innovation. Similarly, social influence was also found to influence the performance expectancy of the innovation. Also, social influence was found to influence the visibility of the innovation.

Lastly, the visibility of the innovation was found to have a significance influence on the facilitating conditions construct.

For additional information, readers are kindly referred to section 7.2 for further discussion of all of the constructs.

9.1.4 The Learning Innovation Adoption Model

The proposed learning innovations adoption model was built on the UTAUT and Rogers's Innovation Diffusion Theory (IDT). However, measures had to be modified to reflect the need to capture information related to multiple innovations rather than one.

Results from analysing the structural models developed by the researcher indicate that both the proposed and post-hoc models explained about or close to 30% (and up to 40% in some cases) of the variance in the behavioural intention to adopt a learning innovation. Considering that this model is significantly different to the original UTAUT model in that it captures information related to multiple innovations from multiple organisations, this explained variance is considered a very good start. It also indicates that there are possibly other constructs influencing the adoption of learning innovations within UK universities. Further information can be found in chapters 6 and 7 of this study.

9.1.5 Moderation and Mediation Testing

A number of moderating effects were found while analysing both models developed and tested in this study. Overall, gender, age, experience, teaching hours, voluntary of adoption, and country all were found moderating some relationships in both models. Other non-significant but noticeable differences were also found. Further information about all significant moderation effects found is available in sections 6.1.3 and 6.2.7. These were also presented in an easy to follow table in section 7.1.3 and discussed in more details in in the same chapter (section 7.3).

Moreover, a number of mediation effects were examined while uncovering relationships and developing the post-hoc model. Eight mediation effects were found in the post-hoc model. These were initially examined in section 6.2.8, summarised in a table 7.4 (section 7.1.4), and then discussed later (section 7.4). Overall, performance expectancy was found to influence quite a number of relationships in the post-hoc model.

9.2 Summary of Practical Recommendations

Based on the findings of this study and in-light of the literature review and the various studies used throughout this study, the researcher formulated and discussed in detail a number of practical implications. These are of high value to individuals and organisations wishing to encourage the adoption of learning innovations. These practical implications are presented in a summary format below. Readers are kindly referred to section 8.3 above for the full discussion.

9.2.1 Top Management Support

Active involvement of top management is critical to driving and encouraging innovation and innovation diffusion within universities. Top management encouragement and support should be clearly reflected in systems (e.g. reward system), policies, and available support.

9.2.2 Time

For innovation to take place, staff members need to be less pressured, motivated, and have some spare time for development and other activities.

9.2.3 Education and Training

Competence-development activities could help to reduce uncertainties and fears associated with new innovations and technologies. Such activities could introduce staff members to new approaches, tools, and technologies that may enhance learning.

9.2.4 Usefulness

For staff members to have a favourable decision with regard to an innovation other individuals are using or the university plans to diffuse further, benefits of using the innovation should be made clear to potential adopters.

9.2.5 Ease

Innovations that are easier to adopt and use are more likely to be adopted. Moreover, if staff members perceive the innovation as being easy to use, they are likely to consider it to be useful.

9.2.6 Flexibility

Staff members may need or prefer to modify or change the innovation or technology to suit the context of the classroom. Being aware of an innovation being flexible and adaptable to their needs can influence their intention to adopt it.

9.2.7 Visibility

The visibility of the innovation is an important factor in the adoption process. It is also possible that the perception of the visibility of an innovation may influence how staff members perceive the available supporting and facilitating conditions.

9.2.8 Facilitating Conditions

To encourage the adoption of certain innovation and technologies, supporting conditions for the use should be in place. The perception of whether or not supporting conditions are provided influences the behavioural intention and the use behaviour of potential adopters.

9.2.9 Motivation

Over-burdened and pressured staff members are unlikely to consider investing in new innovations and technologies that may help them in some way unless they were motivated to do so.

9.2.10 Students' Requirements and Expectations

Staff members' decisions to adopt an innovation are influenced to a certain extent by the degree to which the innovation could help meet or exceed students' requirements and expectations.

9.2.11 Sustainability and wide-spread

For the UK HE sector to gain a competitive advantage, there is need for a sector-wide initiative, aiming to identify effective innovative approaches and technologies that enhance learning which can then be diffused.

♦♦♦ Closing Thought ♦♦♦

Current operational pressures, together with the lack of time available for making improvements in learning outcomes make it unlikely that academic staff members will make significant innovations impacting student' learning. This research indicates that innovation and the diffusion of innovations that would enhance the competitiveness of UK universities require that they nurture their employees and provide support for their creativity.

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Appendices

Appendix 1: Ethical Approval

Wednesday 31st July 2013

Warwick Medical School

PRIVATE
Mr Abdulrahman Hariri
58 Abbey Court
Coventry
CV1 5SA

Dear Abdulrahman

Study Title and BSREC Reference: *Understanding Adoption of Learning Innovations in UK Universities. Validating an Extended UTAUT Model – REGO-2013-030*

I have had the chance to review your latest application to BSREC, along with the feedback you were given on 31st May 2013. You have, in my view, addressed the major concern that BSREC had about the recruitment strategy for participants; you have piloted your survey; and you have provided acceptable justification including sample size calculations for recruiting participants.

My recommendation is that your proposal be given full approval. You may start your study now.

However, please can you write back to me (by email is fine) to briefly state the rationale you will use to decide which departments you intend to approach in which university? If you already know which universities/departments you will recruit, then please inform me of that also. This is so that we can keep a record of the broad pattern of recruitment into studies involving surveys, and to ensure that any one participant group is not overburdened.

BSREC has a responsibility to the university to ensure that all research under its remit is conducted ethically. If, in the Committee's view, a research project has methodological concerns (indiscriminate recruitment of participants is one example) then it is entirely appropriate that these are addressed as a requirement of the research ethics and governance approval processes.

As you have addressed the BSREC concerns about these issues in your study, you are given approval to start. I wish you every success in your research.

Yours sincerely,

Dr David Davies
Chair
Biomedical and Scientific
Research Ethics Sub-Committee

Medical School Building
The University of Warwick
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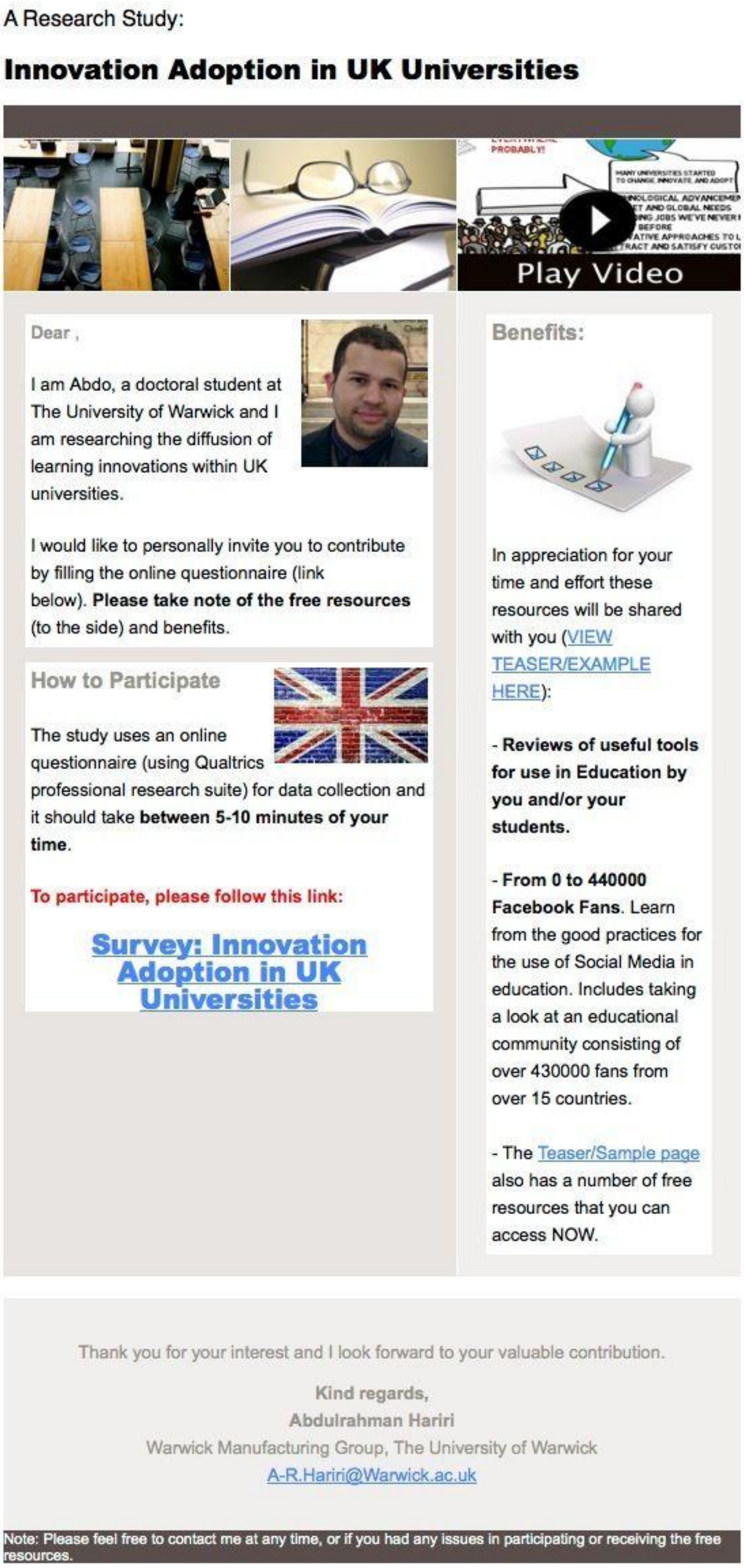
THE UNIVERSITY OF WARWICK

Appendix 2: Invitation and Online Questionnaire

The following is the invitation e-mail used to invite respondents to participate in the study:



A Research Study:

Innovation Adoption in UK Universities

Play Video

Dear ,

I am Abdo, a doctoral student at The University of Warwick and I am researching the diffusion of learning innovations within UK universities.

I would like to personally invite you to contribute by filling the online questionnaire (link below). **Please take note of the free resources** (to the side) and benefits.

How to Participate

The study uses an online questionnaire (using Qualtrics professional research suite) for data collection and it should take **between 5-10 minutes of your time**.

To participate, please follow this link:

Survey: Innovation Adoption in UK Universities

Benefits:

In appreciation for your time and effort these resources will be shared with you (VIEW TEASER/EXAMPLE HERE):

- **Reviews of useful tools for use in Education by you and/or your students.**

- **From 0 to 440000 Facebook Fans**. Learn from the good practices for the use of Social Media in education. Includes taking a look at an educational community consisting of over 430000 fans from over 15 countries.

- The Teaser/Sample page also has a number of free resources that you can access NOW.

Thank you for your interest and I look forward to your valuable contribution.

Kind regards,
Abdulrahman Hariri
Warwick Manufacturing Group, The University of Warwick
A-R.Hariri@Warwick.ac.uk

Note: Please feel free to contact me at any time, or if you had any issues in participating or receiving the free resources.

Below, the questionnaire and the questions used are reported. Please note that some questions are displayed/hidden based on respondents' answers.

Introduction (Part 1)

WMG

THE UNIVERSITY OF WARWICK

Dear ${e://Field/Staff%20Name},

First, I would like to thank you for your interest in this study for contributing today.

This study attempts to collect information about teaching members of staff's perception about innovations that enhance learning and the contributing factors to the adoption and use of such innovations.

When ready, please click NEXT at the bottom of the page to start the questionnaire.

(Optional Video) Learn more about the study

If you haven't already, please feel free to check this short animation video (~3minutes) to learn more about the study and why UK universities need to become more innovative.

Note: I will share with you how to create similar animations!

Research Ethics
All information provided is kept securely and anonymously and cannot be linked to you. Further information can be obtained through the participant information leaflet (Download the leaflet).

Participation in this study is **voluntary** and you may withdraw from the study at anytime by closing this window. If you decide to continue, this will be considered as an agreement to participate and that you have read the information sheet and agree to take part in this study.

All data obtained from participants will be kept **confidential** and will only be reported in an aggregate format.

This questionnaire should take between 10-15 minutes of your time.

Benefits gained by participating:
In appreciation for their valued input, participants will benefit from the following free resources:
- **Reviews of useful tools** that can be used by students and teachers in education.
- **From 0 to more than 440000 Fans**: Access to a presentation sharing experiences gained by the researcher in the past 4 years focusing on using social media in education. This will be presented in addition to a real case of an educational Facebook page that attracted millions of views from over 15 countries.

Once again, Thank you!
The Researcher,
Abdulrahman Hariri (A-R.Hariri@Warwick.ac.uk | Twitter: @aahariri)
Warwick Manufacturing Group,
The University of Warwick,
Coventry, United Kingdom

General Information (Part 2)

Gender
Male Female
Age
Under 30 Years 30-50 Years Over 50 Years
Total years of work experience at university level (Note: this is general and not just teaching-related)
Less than 5 years

5-9 years More than 9 years
How many preparation and delivery hours associated with teaching do you have per academic year (Excluding marking and administration)?
Less than 50 hours/year 51-500 hours/year 501-1000 hours/year Greater than 1000 hours/year
Education Level
University diploma or bachelor Masters Doctorate Other. Please specify
Place of work (Country)?
England Northern Ireland Scotland Wales
At which university do you currently work? (Drop-down selection)
Academic Department (Text entry)

Important Definitions

Learning Innovation:
A learning innovation is an innovation (something new or applied in a new way), good practice, a new approach or technology that enhance students' learning when used.

What constitutes an approach being innovative in UK universities?
Approaches, technologies, or methods that were not previously used within UK universities are all considered innovative.

Examples of learning innovations:

- Use of learning management systems (Moodle, BlackBoard, etc...) or similar technologies to offer or deliver content in a new way.
- Testing a new approach to seminars.
- Creating a new innovative learning envrionment for students.
- Use of blogs, wikis, and online forums to facilitate discussions and interaction between students.
- Use of information technologies to deliver courses or knowledge to new places or the whole world freely or for a price (e.g. iTunes University, Coursera, Udacity, Udemy, edX).

Have you previously adopted any innovation, technology or good practice that enhances learning?
Yes No
Keeping in mind one learning innovation that you have adopted, please answer the following question to help us understand what affects your decision to adopt or reject a learning innovation
Where you forced in any way to adopt the learning innovation in question? For example, if this was mandated by the management.
Yes, I was asked to do it No, my decision was voluntary
Briefly, please explain what led you to adopt and use this learning innovation (Text entry).
Note: This question changes to why didn't you adopt a learning innovation if the respondent did not adopt any innovation, technology, or good practice that enhances learning.
(If an adopter) For how long have you been using this learning innovation?
Less than 2 years

2 to 5 years More than 5 years

Constructs (Part 3)

At the point of adopting the learning innovation, what was your perception of the following:

Performance Expectancy
-I would find that using a learning innovation is useful in my job
-Using a learning innovation would enable me to accomplish tasks more quickly
-Using a learning innovation would increase my productivity.
-Using a learning innovation would make it easier for me to do my job.
Effort Expectancy
-Learning to use the learning innovation must be easy.
-I would find the learning innovation easy to use.
-The approach to use the learning innovation must be clear and understandable to me.
-It would be easy to become skilful at using a learning innovation.
-The use of the learning innovation does not take much effort.
-The use of the learning innovation does not require too much time.
Social Influence
-People who influence my behaviour think that I should use the learning innovation.
-People who are important to me think that I should use the learning innovation.
-I would use the learning innovation because of the proportion of co-workers who use it.
-The senior management would be helpful in the use of the learning innovation.

-The organization has supported the use of the learning innovation.
-Using the learning innovation would improve my image within the organization.
-People in my organization who use the learning innovation have more prestige than those who do not.
Facilitating Conditions
-I have control over using any learning innovation I see fit.
-I have the resources necessary to use the learning innovation I see fit.
-I have the knowledge necessary to use the learning innovation I see fit.
-Guidance is available to me for the selection of the appropriate learning innovation that I could use.
Results Demonstrability
-The results of using the learning innovation by myself or others are clear to me.
-I would have no difficulty in telling others about the results of the learning innovation I use.
-I believe I could communicate to others the consequences of using the learning innovation
Visibility
-I have seen what others are doing with the learning innovations they are using.
-Learning innovations are not very visible in my organization.
-It is easy for me to observe others using learning innovations in my organisation.
-Effective learning innovations in my organization are disseminated for others to learn from.
Trialability
-I’ve had a great deal of opportunities to try various learning innovations.
-I know exactly what I can do If I wanted to try out a learning innovation.
-The ability to try a learning innovation before using it is important to me.

-I am likely to use learning innovations that have been tested and proven effective by others in my area.
-I am likely to use learning innovations tested and proved to be effective by myself.
Reinvention
-It must be easy to change the learning innovation I would use to do what I want it to do.
-I am more inclined to use a learning innovation that I am able to change or adjust to suit my needs.
-I am more likely to adopt and use a learning innovation when I am actively involved in customizing it to fit my unique situation.
Students’ Requirements and Expectations
-Before deciding to use a learning innovation, it must be clear how it can help me meet or exceed my students' expectations.
-Knowing about my students’ requirements allows me to use an appropriate learning innovation.
-Using a learning innovation helps me meet or exceed my students’ expectations.
-The choice of what learning innovation I use is not dependent on whether it can help me fulfil my students' requirements or not.
Students’ Learning
-Before deciding to use a learning innovation, it must be clear how it can improve students' learning.
-The learning innovation I use must help improve students' learning.
-Understanding how my students learn best will help me to use the appropriate learning innovation.
-I evaluate the learning innovation I use to ensure that it enhances my students’ learning.
Behavioural Intention

-I intend to use a learning innovation in the near future.
-I predict I would use a learning innovation in the near future.
-I plan to use a learning innovation in the near future.

Appendix 3: Variables Lookup Tables

The following tables serve as lookup tables for the various variables used in the thesis and the various tests reported below.

Short Name	Variable Name	Notes
PE	Performance Expectancy	
EE	Effort Expectancy	
T	Trialability	Was combined with another variable
FC	Facilitating Conditions	Was combined with another variable
TandFC	-	The variables T and FC combined
V	Visibility	
ReInv	Reinvention	
SI	Social Influence	Was split into two variables
SI_IMG	Social Image	Resulted after splitting SI into two different factors. Concerned with the image.
SI_INF	Social Influence	Resulted after splitting SI into two different factors. Concerned with the influence.
SL	Students' Learning	
SRE	Students' Requirements and Expectations	
RD	Results Demonstrability	
BI	Behavioural Intention	
Use	Actual Use	

Performance Expectancy (PE)	
PE_1	I would find that using a learning innovation is useful in my job
PE_2	Using a learning innovation would enable me to accomplish tasks more quickly
PE_3	Using a learning innovation would increase my productivity.
PE_4	Using a learning innovation would make it easier for me to do my job.
Effort Expectancy (EE)	
EE_1	Learning to use the learning innovation must be easy.
EE_2	I would find the learning innovation easy to use.
EE_3	The approach to use the learning innovation must be clear and understandable to me.
EE_4	It would be easy to become skilful at using a learning innovation.
EE_5	The use of the learning innovation does not take much effort.
EE_6	The use of the learning innovation does not require too much time.
Social Influence (SI)	
SI_1	People who influence my behaviour think that I should use the learning innovation.
SI_2	People who are important to me think that I should use the learning innovation.
SI_3	I would use the learning innovation because of the proportion of co-workers who use it.
SI_4	The senior management would be helpful in the use of the learning innovation.
SI_5	The organization has supported the use of the learning innovation.
SI_6	Using the learning innovation would improve my image within the organization.
SI_7	People in my organization who use the learning innovation have more prestige than those who do not.
Facilitating Conditions (FC)	
FC_1	I have control over using any learning innovation I see fit.
FC_2	I have the resources necessary to use the learning innovation I see fit.
FC_3	I have the knowledge necessary to use the learning innovation I see

	fit.
FC_4	Guidance is available to me for the selection of the appropriate learning innovation that I could use.
Results Demonstrability (RD)	
RD_1	The results of using the learning innovation by myself or others are clear to me.
RD_2	I would have no difficulty in telling others about the results of the learning innovation I use.
RD_3	I believe I could communicate to others the consequences of using the learning innovation
Visibility (V)	
V_1	I have seen what others are doing with the learning innovations they are using.
V_2	Learning innovations are not very visible in my organization.
V_3	It is easy for me to observe others using learning innovations in my organisation.
V_4	Effective learning innovations in my organization are disseminated for others to learn from.
Trialability (T)	
T_1	I've had a great deal of opportunities to try various learning innovations.
T_2	I know exactly what I can do If I wanted to try out a learning innovation.
T_3	The ability to try a learning innovation before using it is important to me.
T_4	I am likely to use learning innovations that have been tested and proven effective by others in my area.
T_5	I am likely to use learning innovations tested and proved to be effective by myself.
Reinvention (ReInv)	
ReInv_1	It must be easy to change the learning innovation I would use to do what I want it to do.
ReInv_2	I am more inclined to use a learning innovation that I am able to

	change or adjust to suit my needs.
ReInv_3	I am more likely to adopt and use a learning innovation when I am actively involved in customizing it to fit my unique situation.
Students' Requirements and Expectations (SRE)	
SRE_1	Before deciding to use a learning innovation, it must be clear how it can help me meet or exceed my students' expectations.
SRE_2	Knowing about my students' requirements allows me to use an appropriate learning innovation.
SRE_3	Using a learning innovation helps me meet or exceed my students' expectations.
SRE_4	The choice of what learning innovation I use is not dependent on whether it can help me fulfil my students' requirements or not.
Students' Learning (SL)	
SL_1	Before deciding to use a learning innovation, it must be clear how it can improve students' learning.
SL_2	The learning innovation I use must help improve students' learning.
SL_3	Understanding how my students learn best will help me to use the appropriate learning innovation.
SL_4	I evaluate the learning innovation I use to ensure that it enhances my students' learning.
Behavioural Intention (BI)	
BI_1	I intend to use a learning innovation in the near future.
BI_2	I predict I would use a learning innovation in the near future.
BI_3	I plan to use a learning innovation in the near future.

Appendix 4: Homogeneity Test of Adopters/Non-Adopters

	Levene Statistic	df1	df2	Sig.
PE_1	19.567	1	495	.000
PE_2	.246	1	495	.620
PE_3	.071	1	495	.790
PE_4	4.916	1	495	.027
EE_1	.447	1	495	.504
EE_2	.000	1	495	.998
EE_3	.194	1	495	.660
EE_4	.271	1	495	.603
EE_5	.999	1	495	.318
EE_6	.009	1	495	.925
SI_1	1.113	1	495	.292
SI_2	.013	1	495	.910
SI_3	2.911	1	495	.089
SI_4	.105	1	495	.746
SI_5	1.533	1	495	.216
SI_6	1.358	1	495	.244
SI_7	.019	1	495	.891
FC_1	.010	1	495	.922
FC_2	.451	1	495	.502
FC_3	1.715	1	495	.191
FC_4	.001	1	495	.974
RD_1	.770	1	495	.381
RD_2	26.567	1	495	.000
RD_3	25.812	1	495	.000
V_1	3.911	1	495	.049
V_2	.960	1	495	.328
V_3	.988	1	495	.321
V_4	5.805	1	495	.016

T_1	1.240	1	495	.266
T_2	.319	1	495	.573
T_3	2.564	1	495	.110
T_4	1.792	1	495	.181
T_5	6.184	1	495	.013
RelInv_1	.054	1	495	.816
RelInv_2	11.525	1	495	.001
RelInv_3	.353	1	495	.553
SRE_1	8.297	1	495	.004
SRE_2	24.091	1	495	.000
SRE_3	9.754	1	495	.002
SRE_4	5.757	1	495	.017
SL_1	4.551	1	495	.033
SL_2	12.236	1	495	.001
SL_3	17.525	1	495	.000
SL_4	.001	1	495	.970
BI_1	15.114	1	495	.000
BI_2	28.766	1	495	.000
BI_3	7.797	1	495	.005

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PE_1	Between Groups	64.922	1	64.922	57.403	.000
	Within Groups	559.835	495	1.131		
	Total	624.757	496			
PE_2	Between Groups	28.237	1	28.237	13.301	.000
	Within Groups	1050.901	495	2.123		
	Total	1079.139	496			
PE_3	Between Groups	28.818	1	28.818	13.789	.000
	Within Groups	1034.490	495	2.090		
	Total	1063.308	496			
PE_4	Between Groups	43.150	1	43.150	20.892	.000
	Within Groups	1022.363	495	2.065		
	Total	1065.513	496			
EE_1	Between Groups	.025	1	.025	.011	.916
	Within Groups	1090.418	495	2.203		
	Total	1090.443	496			
EE_2	Between Groups	25.325	1	25.325	17.868	.000
	Within Groups	701.589	495	1.417		
	Total	726.913	496			

EE_3	Between Groups	.010	1	.010	.010	.920
	Within Groups	503.957	495	1.018		
	Total	503.968	496			
EE_4	Between Groups	28.227	1	28.227	18.787	.000
	Within Groups	743.741	495	1.503		
	Total	771.968	496			
EE_5	Between Groups	1.914	1	1.914	.730	.393
	Within Groups	1297.692	495	2.622		
	Total	1299.606	496			
EE_6	Between Groups	1.484	1	1.484	.513	.474
	Within Groups	1431.373	495	2.892		
	Total	1432.857	496			
SI_1	Between Groups	15.725	1	15.725	7.360	.007
	Within Groups	1057.627	495	2.137		
	Total	1073.352	496			
SI_2	Between Groups	47.824	1	47.824	24.408	.000
	Within Groups	969.886	495	1.959		
	Total	1017.710	496			
SI_3	Between Groups	1.208	1	1.208	.459	.498
	Within Groups	1301.577	495	2.629		
	Total	1302.785	496			
SI_4	Between Groups	7.070	1	7.070	2.861	.091
	Within Groups	1223.485	495	2.472		
	Total	1230.555	496			
SI_5	Between Groups	7.681	1	7.681	4.048	.045
	Within Groups	939.301	495	1.898		
	Total	946.982	496			
SI_6	Between Groups	11.450	1	11.450	6.878	.009
	Within Groups	823.979	495	1.665		
	Total	835.429	496			
SI_7	Between Groups	2.172	1	2.172	1.093	.296
	Within Groups	983.586	495	1.987		
	Total	985.759	496			
FC_1	Between Groups	4.819	1	4.819	2.126	.145
	Within Groups	1121.717	495	2.266		
	Total	1126.535	496			
FC_2	Between Groups	5.388	1	5.388	2.523	.113
	Within Groups	1056.990	495	2.135		
	Total	1062.378	496			
FC_3	Between Groups	70.265	1	70.265	34.764	.000
	Within Groups	1000.495	495	2.021		
	Total	1070.761	496			
FC_4	Between Groups	18.482	1	18.482	9.956	.002
	Within Groups	918.926	495	1.856		
	Total	937.408	496			
RD_1	Between Groups	96.735	1	96.735	61.223	.000
	Within Groups	782.122	495	1.580		
	Total	878.857	496			
RD_2	Between Groups	42.444	1	42.444	28.999	.000
	Within Groups	724.498	495	1.464		
	Total	766.942	496			
RD_3	Between Groups	46.355	1	46.355	35.991	.000
	Within Groups	637.544	495	1.288		
	Total	683.899	496			
V_1	Between Groups	26.712	1	26.712	13.600	.000
	Within Groups	972.213	495	1.964		
	Total	998.926	496			
V_2	Between Groups	18.734	1	18.734	8.235	.004

	Within Groups	1126.107	495	2.275		
	Total	1144.841	496			
V_3	Between Groups	13.734	1	13.734	6.743	.010
	Within Groups	1008.194	495	2.037		
	Total	1021.928	496			
V_4	Between Groups	5.957	1	5.957	2.820	.094
	Within Groups	1045.556	495	2.112		
	Total	1051.513	496			
T_1	Between Groups	53.829	1	53.829	23.781	.000
	Within Groups	1120.449	495	2.264		
	Total	1174.278	496			
T_2	Between Groups	33.884	1	33.884	15.110	.000
	Within Groups	1109.988	495	2.242		
	Total	1143.871	496			
T_3	Between Groups	6.816	1	6.816	4.921	.027
	Within Groups	685.575	495	1.385		
	Total	692.390	496			
T_4	Between Groups	1.915	1	1.915	1.132	.288
	Within Groups	837.364	495	1.692		
	Total	839.280	496			
T_5	Between Groups	14.276	1	14.276	13.551	.000
	Within Groups	521.467	495	1.053		
	Total	535.742	496			
ReInv_1	Between Groups	14.149	1	14.149	10.311	.001
	Within Groups	679.215	495	1.372		
	Total	693.364	496			
ReInv_2	Between Groups	13.137	1	13.137	15.435	.000
	Within Groups	421.325	495	.851		
	Total	434.463	496			
ReInv_3	Between Groups	6.406	1	6.406	5.790	.016
	Within Groups	547.679	495	1.106		
	Total	554.085	496			
SRE_1	Between Groups	2.285	1	2.285	2.173	.141
	Within Groups	520.685	495	1.052		
	Total	522.970	496			
SRE_2	Between Groups	23.093	1	23.093	27.074	.000
	Within Groups	422.215	495	.853		
	Total	445.308	496			
SRE_3	Between Groups	56.835	1	56.835	44.648	.000
	Within Groups	630.107	495	1.273		
	Total	686.942	496			
SRE_4	Between Groups	.432	1	.432	.149	.700
	Within Groups	1438.264	495	2.906		
	Total	1438.696	496			
SL_1	Between Groups	2.243	1	2.243	2.515	.113
	Within Groups	441.523	495	.892		
	Total	443.767	496			
SL_2	Between Groups	10.747	1	10.747	11.298	.001
	Within Groups	470.859	495	.951		
	Total	481.606	496			
SL_3	Between Groups	12.281	1	12.281	13.361	.000
	Within Groups	454.998	495	.919		
	Total	467.280	496			
SL_4	Between Groups	22.577	1	22.577	16.907	.000
	Within Groups	661.021	495	1.335		
	Total	683.598	496			
BI_1	Between Groups	74.536	1	74.536	53.608	.000
	Within Groups	688.248	495	1.390		

	Total	762.785	496			
BI_2	Between Groups	90.598	1	90.598	73.752	.000
	Within Groups	608.062	495	1.228		
	Total	698.660	496			
BI_3	Between Groups	89.212	1	89.212	59.499	.000
	Within Groups	742.192	495	1.499		
	Total	831.404	496			

Robust Tests of Equality of Means

		Statistic[a]	df1	df2	Sig.
PE_1	Welch	29.228	1	46.699	.000
	Brown-Forsythe	29.228	1	46.699	.000
PE_2	Welch	11.337	1	50.126	.001
	Brown-Forsythe	11.337	1	50.126	.001
PE_3	Welch	11.280	1	49.767	.002
	Brown-Forsythe	11.280	1	49.767	.002
PE_4	Welch	14.853	1	48.671	.000
	Brown-Forsythe	14.853	1	48.671	.000
EE_1	Welch	.010	1	50.252	.922
	Brown-Forsythe	.010	1	50.252	.922
EE_2	Welch	16.990	1	51.177	.000
	Brown-Forsythe	16.990	1	51.177	.000
EE_3	Welch	.010	1	51.898	.919
	Brown-Forsythe	.010	1	51.898	.919
EE_4	Welch	16.663	1	50.491	.000
	Brown-Forsythe	16.663	1	50.491	.000
EE_5	Welch	.801	1	52.791	.375
	Brown-Forsythe	.801	1	52.791	.375
EE_6	Welch	.481	1	51.030	.491
	Brown-Forsythe	.481	1	51.030	.491
SI_1	Welch	8.807	1	53.940	.004
	Brown-Forsythe	8.807	1	53.940	.004
SI_2	Welch	24.308	1	51.667	.000
	Brown-Forsythe	24.308	1	51.667	.000

SI_3	Welch	.619	1	55.742	.435
	Brown-Forsythe	.619	1	55.742	.435
SI_4	Welch	3.288	1	53.394	.075
	Brown-Forsythe	3.288	1	53.394	.075
SI_5	Welch	5.010	1	54.422	.029
	Brown-Forsythe	5.010	1	54.422	.029
SI_6	Welch	5.076	1	48.944	.029
	Brown-Forsythe	5.076	1	48.944	.029
SI_7	Welch	1.088	1	51.661	.302
	Brown-Forsythe	1.088	1	51.661	.302
FC_1	Welch	2.470	1	53.533	.122
	Brown-Forsythe	2.470	1	53.533	.122
FC_2	Welch	2.299	1	50.750	.136
	Brown-Forsythe	2.299	1	50.750	.136
FC_3	Welch	29.317	1	50.031	.000
	Brown-Forsythe	29.317	1	50.031	.000
FC_4	Welch	10.603	1	52.434	.002
	Brown-Forsythe	10.603	1	52.434	.002
RD_1	Welch	51.167	1	49.952	.000
	Brown-Forsythe	51.167	1	49.952	.000
RD_2	Welch	14.520	1	46.619	.000
	Brown-Forsythe	14.520	1	46.619	.000
RD_3	Welch	17.194	1	46.402	.000
	Brown-Forsythe	17.194	1	46.402	.000
V_1	Welch	10.422	1	49.233	.002
	Brown-Forsythe	10.422	1	49.233	.002
V_2	Welch	8.984	1	52.726	.004
	Brown-Forsythe	8.984	1	52.726	.004
V_3	Welch	7.084	1	52.273	.010
	Brown-Forsythe	7.084	1	52.273	.010
V_4	Welch	3.561	1	54.719	.064
	Brown-Forsythe	3.561	1	54.719	.064

T_1	Welch	24.161	1	51.889	.000
	Brown-Forsythe	24.161	1	51.889	.000
T_2	Welch	13.541	1	50.589	.001
	Brown-Forsythe	13.541	1	50.589	.001
T_3	Welch	3.834	1	49.365	.056
	Brown-Forsythe	3.834	1	49.365	.056
T_4	Welch	.801	1	48.639	.375
	Brown-Forsythe	.801	1	48.639	.375
T_5	Welch	9.306	1	48.428	.004
	Brown-Forsythe	9.306	1	48.428	.004
RelInv_1	Welch	9.594	1	50.956	.003
	Brown-Forsythe	9.594	1	50.956	.003
RelInv_2	Welch	11.149	1	48.785	.002
	Brown-Forsythe	11.149	1	48.785	.002
RelInv_3	Welch	5.773	1	51.681	.020
	Brown-Forsythe	5.773	1	51.681	.020
SRE_1	Welch	1.204	1	47.127	.278
	Brown-Forsythe	1.204	1	47.127	.278
SRE_2	Welch	13.713	1	46.673	.001
	Brown-Forsythe	13.713	1	46.673	.001
SRE_3	Welch	24.151	1	47.001	.000
	Brown-Forsythe	24.151	1	47.001	.000
SRE_4	Welch	.224	1	57.740	.638
	Brown-Forsythe	.224	1	57.740	.638
SL_1	Welch	1.990	1	49.492	.165
	Brown-Forsythe	1.990	1	49.492	.165
SL_2	Welch	7.168	1	47.909	.010
	Brown-Forsythe	7.168	1	47.909	.010
SL_3	Welch	7.414	1	47.135	.009
	Brown-Forsythe	7.414	1	47.135	.009
SL_4	Welch	18.873	1	53.014	.000
	Brown-Forsythe	18.873	1	53.014	.000

BI_1	Welch	29.019	1	47.005	.000
	Brown-Forsythe	29.019	1	47.005	.000
BI_2	Welch	32.383	1	46.041	.000
	Brown-Forsythe	32.383	1	46.041	.000
BI_3	Welch	35.558	1	47.549	.000
	Brown-Forsythe	35.558	1	47.549	.000
a. Asymptotically F distributed.					

Appendix 5: EFA Pattern Matrix, Factor Correlation Matrix, and Cronbach's Alpha

Communalities[a]

	Initial	Extraction
PE_2	.730	.714
PE_3	.744	**.999**
EE_2	.488	.375
EE_4	.602	.513
EE_5	.768	.889
EE_6	.744	.806
SI_1	.669	.815
SI_2	.672	.783
SI_3	.333	.318
SI_6	.442	.500
SI_7	.406	.796
FC_1	.398	.349
FC_2	.533	.521
FC_3	.535	.531
RD_1	.564	.550
RD_2	.764	.861
RD_3	.740	.821
V_1	.469	.511
V_3	.584	.749
V_4	.499	.565
T_1	.634	.653
T_2	.643	.668
ReInv_1	.349	.381
ReInv_2	.520	.764
ReInv_3	.433	.483
SRE_1	.415	.444
SRE_2	.576	.735
SRE_3	.534	.530
SL_1	.576	.625
SL_2	.629	.833
SL_3	.587	.599
SL_4	.466	.433
BI_1	.875	.925
BI_2	.857	.889
BI_3	.838	.868

Extraction Method: Maximum Likelihood.
a. One or more communalitiy estimates greater than 1 were encountered during iterations. The resulting solution should be interpreted with caution.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7.829	22.368	22.368	3.463	9.893	9.893	4.809
2	3.401	9.717	32.085	4.508	12.881	22.774	4.497
3	2.627	7.507	39.592	2.955	8.443	31.218	3.025
4	2.547	7.276	46.868	2.147	6.133	37.351	3.856
5	2.206	6.303	53.170	2.372	6.778	44.129	3.708
6	1.713	4.895	58.066	2.349	6.711	50.840	5.223
7	1.424	4.070	62.135	1.368	3.908	54.749	2.350
8	1.347	3.848	65.984	1.148	3.281	58.029	2.290
9	1.179	3.367	69.351	.960	2.744	60.773	3.620
10	1.108	3.165	72.516	.885	2.528	63.302	4.032
11	.933	2.666	75.183	.640	1.828	65.129	2.153
12	.710	2.029	77.212				
13	.663	1.895	79.107				
14	.642	1.835	80.942				
15	.619	1.769	82.711				
16	.605	1.729	84.441				
17	.531	1.518	85.958				
18	.483	1.379	87.337				
19	.449	1.284	88.621				
20	.420	1.200	89.821				
21	.389	1.111	90.932				
22	.378	1.080	92.013				
23	.357	1.020	93.032				
24	.342	.978	94.010				
25	.294	.839	94.850				
26	.277	.792	95.642				

27	.260	.744	96.386				
28	.244	.697	97.083				
29	.219	.626	97.709				
30	.192	.548	98.257				
31	.160	.458	98.715				
32	.134	.383	99.098				
33	.127	.363	99.461				
34	.107	.307	99.768				
35	.081	.232	100.000				

Extraction Method: Maximum Likelihood.
a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Pattern Matrix

	Factor										
	1	2	3	4	5	6	7	8	9	10	11
Cronbach's Alpha	**.960**	**.825**	**.849**	**.820**	**.810**	**.857**	**.762**	**.737**	**.909**	**.747**	**.741**
BI_1	.994										
BI_3	.964										
BI_2	.962										
FC_2		.824									
FC_1		.681									
T_2		.669									
T_1		.652									
FC_3		.643									
EE_5			.953								
EE_6			.907								
EE_4			.614								
EE_2			.525								

SL_2				.995							
SL_1				.808							
SL_3				.536							
SL_4				.372							
V_3					.900						
V_4					.751						
V_1					.698						
RD_3						.993					
RD_2						.981					
RD_1						.507					
SI_1							.901				
SI_2							.872				
SI_3							.424				
ReInv_2								.880			
ReInv_3								.666			
ReInv_1								.601			
PE_3									1.029		
PE_2									.826		
SRE_2										.807	
SRE_1										.647	
SRE_3										.448	
SI_7											.927
SI_6											.618

Extraction Method: Maximum Likelihood.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

Factor Correlation Matrix

Factor	1	2	3	4	5	6	7	8	9	10	11
1	1.000	.313	.087	.292	.227	.502	.158	.294	.411	.398	.216
2	.313	1.000	.240	.162	.535	.550	.029	.030	.294	.204	.085
3	.087	.240	1.000	.078	.184	.201	.068	.081	.267	.116	.010
4	.292	.162	.078	1.000	.171	.393	.026	.231	.242	.589	.213
5	.227	.535	.184	.171	1.000	.354	.200	-.043	.261	.118	.237
6	.502	.550	.201	.393	.354	1.000	.073	.221	.355	.449	.187
7	.158	.029	.068	.026	.200	.073	1.000	.065	.235	.143	.365
8	.294	.030	.081	.231	-.043	.221	.065	1.000	.089	.247	.079
9	.411	.294	.267	.242	.261	.355	.235	.089	1.000	.372	.186
10	.398	.204	.116	.589	.118	.449	.143	.247	.372	1.000	.201
11	.216	.085	.010	.213	.237	.187	.365	.079	.186	.201	1.000

Extraction Method: Maximum Likelihood.

Rotation Method: Promax with Kaiser Normalization.

Reproduced Correlations

Variables	PE_2	PE_3	EE_2	EE_4	EE_5	EE_6	SI_1	SI_2	SI_3	SI_6	SI_7	FC_1	FC_2	FC_3	RD_1	RD_2	RD_3	V_1
PE_2	.71[a]	.834	.252	.257	.239	.242	.17	.247	.126	.137	.120	.142	.139	.157	.309	.167	.180	.193
PE_3	.834	1.0[a]	.243	.236	.172	.178	.15	.262	.101	.154	.131	.174	.161	.179	.374	.234	.253	.215
EE_2	.252	.243	.38[a]	.422	.511	.483	.05	.111	.071	.073	.035	.100	.081	.190	.218	.241	.224	.125
EE_4	.257	.236	.422	.51[a]	.596	.566	.00	.077	.073	.109	.087	.152	.154	.282	.285	.308	.288	.202
EE_5	.239	.172	.511	.596	.89[a]	.843	.0	.006	.100	-.06	-.06	.115	.135	.221	.162	.119	.079	.074
EE_6	.242	.178	.483	.566	.843	.81[a]	.03	.036	.116	-.03	-.02	.110	.134	.210	.170	.122	.084	.069
SI_1	.168	.154	.051	.001	-.01	.025	.8[a]	.762	.434	.286	.263	-.03	.049	-.004	.109	-.01	-.03	.182
SI_2	.247	.262	.111	.077	.006	.036	.76	.783[a]	.385	.304	.242	.053	.126	.106	.252	.196	.175	.231
SI_3	.126	.101	.071	.073	.100	.116	.43	.385	.318[a]	.205	.236	-.03	.016	-.022	.035	-.08	-.09	.143
SI_6	.137	.154	.073	.109	-.06	-.03	.29	.304	.205	.50[a]	.591	.049	.015	.088	.161	.171	.200	.170
SI_7	.120	.131	.035	.087	-.06	-.02	.26	.242	.236	.591	.80[a]	.042	.002	.048	.102	.082	.123	.102
FC_1	.142	.174	.100	.152	.115	.110	.0	.053	-.034	.049	.042	.35[a]	.402	.396	.265	.251	.214	.110
FC_2	.139	.161	.081	.154	.135	.134	.05	.126	.016	.015	.002	.402	.52[a]	.478	.312	.249	.194	.196
FC_3	.157	.179	.190	.282	.221	.210	.00	.106	-.022	.088	.048	.396	.478	.531[a]	.401	.408	.365	.278
RD_1	.309	.374	.218	.285	.162	.170	.11	.252	.035	.161	.102	.265	.312	.401	.550[a]	.614	.583	.305
RD_2	.167	.234	.241	.308	.119	.122	.0	.196	-.081	.171	.082	.251	.249	.408	.614	.86[a]	.834	.246
RD_3	.180	.253	.224	.288	.079	.084	.0	.175	-.093	.200	.123	.214	.194	.365	.583	.834	.821[a]	.240
V_1	.193	.215	.125	.202	.074	.069	.18	.231	.143	.170	.102	.110	.196	.278	.305	.246	.240	.51[a]
V_3	.185	.197	.115	.234	.101	.094	.11	.164	.149	.161	.111	.107	.225	.299	.297	.216	.215	.592
V_4	.196	.215	.102	.202	.068	.065	.11	.152	.141	.191	.160	.121	.212	.280	.276	.190	.189	.519
T_1	.160	.193	.113	.224	.085	.077	.02	.123	.015	.151	.115	.388	.496	.538	.369	.336	.308	.413
T_2	.172	.208	.150	.261	.151	.138	-.1	.076	-.047	.066	.005	.414	.520	.569	.408	.404	.367	.371
ReInv_1	.025	.032	.178	.144	.146	.111	.04	.072	.038	.053	-.01	.010	-.06	.021	.011	.087	.075	.034
ReInv_2	.030	.074	.157	.090	.005	-.04	.02	.090	-.015	.085	-.02	.051	-.06	.041	.033	.176	.167	.017
ReInv_3	.076	.121	.142	.095	.012	-.02	.02	.099	-.008	.101	.023	.083	-.01	.070	.077	.194	.184	.006
SRE_1	.165	.191	.083	.089	.018	.025	.08	.117	.120	.125	.100	.040	.022	.048	.242	.231	.203	.125
SRE_2	.227	.275	.112	.125	.030	.035	.03	.109	.087	.113	.067	.161	.147	.170	.362	.360	.311	.137
SRE_3	.303	.373	.170	.190	.059	.069	.05	.163	.031	.185	.141	.185	.157	.240	.441	.488	.464	.167
SL_1	.135	.139	.094	.125	.00	.000	.0	.075	.070	.146	.075	.038	-.01	.024	.156	.199	.188	.054
SL_2	.152	.153	.133	.178	.027	.027	-.1	.081	.049	.164	.068	.056	.005	.058	.198	.272	.263	.068
SL_3	.177	.193	.141	.168	.032	.034	.04	.136	.095	.215	.153	.099	.051	.112	.263	.300	.278	.114
SL_4	.210	.259	.113	.154	.00	.000	-.1	.058	-.023	.134	.063	.177	.155	.220	.346	.405	.387	.147
BI_1	.314	.372	.193	.180	.010	.010	.12	.199	-.038	.231	.105	.150	.079	.254	.344	.350	.365	.225
BI_2	.286	.339	.187	.169	.00	.00	.16	.229	-.011	.249	.122	.132	.061	.236	.331	.342	.355	.236
BI_3	.310	.364	.191	.184	.027	.026	.12	.194	-.034	.209	.083	.168	.113	.276	.347	.340	.349	.234

Variables	V_3	V_4	T_1	T_2	ReInv_1	ReInv_2	ReInv_3	SRE_1	SRE_2	SRE_3	SL_1	SL_2	SL_3	SL_4	BI_1	BI_2	BI_3
PE_2	.185	.196	.160	.172	.025	.030	.076	.165	.227	.303	.135	.152	.177	.210	.314	.286	.310
PE_3	.197	.215	.193	.208	.032	.074	.121	.191	.275	.373	.139	.153	.193	.259	.372	.339	.364
EE_2	.115	.102	.113	.150	.178	.157	.142	.083	.112	.170	.094	.133	.141	.113	.193	.187	.191
EE_4	.234	.202	.224	.261	.144	.090	.095	.089	.125	.190	.125	.178	.168	.154	.180	.169	.184
EE_5	.101	.068	.085	.151	.146	.005	.012	.018	.030	.059	-.001	.027	.032	.00	.010	.00	.027
EE_6	.094	.065	.077	.138	.111	-.036	-.02	.025	.035	.069	.000	.027	.034	.000	.010	.00	.026
SI_1	.113	.109	.017	-.054	.044	.017	.020	.077	.026	.052	-.027	-.054	.039	-.07	.124	.162	.121
SI_2	.164	.152	.123	.076	.072	.090	.099	.117	.109	.163	.075	.081	.136	.058	.199	.229	.194
SI_3	.149	.141	.015	-.047	.038	-.015	-.01	.120	.087	.031	.070	.049	.095	-.02	-.038	-.01	-.034
SI_6	.161	.191	.151	.066	.053	.085	.101	.125	.113	.185	.146	.164	.215	.134	.231	.249	.209
SI_7	.111	.160	.115	.005	-.012	-.019	.023	.100	.067	.141	.075	.068	.153	.063	.105	.122	.083
FC_1	.107	.121	.388	.414	.010	.051	.083	.040	.161	.185	.038	.056	.099	.177	.150	.132	.168
FC_2	.225	.212	.496	.520	-.063	-.065	-.01	.022	.147	.157	-.007	.005	.051	.155	.079	.061	.113
FC_3	.299	.280	.538	.569	.021	.041	.070	.048	.170	.240	.024	.058	.112	.220	.254	.236	.276
RD_1	.297	.276	.369	.408	.011	.033	.077	.242	.362	.441	.156	.198	.263	.346	.344	.331	.347
RD_2	.216	.190	.336	.404	.087	.176	.194	.231	.360	.488	.199	.272	.300	.405	.350	.342	.340
RD_3	.215	.189	.308	.367	.075	.167	.184	.203	.311	.464	.188	.263	.278	.387	.365	.355	.349
V_1	.592	.519	.413	.371	.034	.017	.006	.125	.137	.167	.054	.068	.114	.147	.225	.236	.234
V_3	.749[a]	.640	.493	.442	-.037	-.098	-.09	.092	.084	.100	.080	.106	.090	.140	.089	.097	.108
V_4	.640	.565[a]	.448	.394	-.012	-.050	-.04	.123	.133	.140	.089	.106	.125	.156	.149	.156	.163
T_1	.493	.448	.65[a]	.643	-.010	.016	.042	.016	.112	.173	.036	.070	.092	.206	.200	.189	.226
T_2	.442	.394	.643	.668[a]	-.020	.004	.038	.004	.119	.195	.036	.083	.086	.231	.213	.192	.241
ReInv_1	-.037	-.012	-.01	-.020	.381[a]	.515	.394	.109	.141	.097	.067	.055	.134	.040	.126	.154	.110
ReInv_2	-.098	-.050	.016	.004	.515	.764[a]	.598	.146	.217	.171	.126	.116	.211	.112	.221	.256	.194
ReInv_3	-.088	-.042	.042	.038	.394	.598	.48[a]	.143	.219	.188	.155	.158	.221	.144	.201	.224	.180
SRE_1	.092	.123	.016	.004	.109	.146	.143	.44[a]	.552	.399	.341	.338	.433	.322	.193	.207	.187
SRE_2	.084	.133	.112	.119	.141	.217	.219	.552	.735[a]	.547	.433	.435	.559	.457	.280	.288	.278
SRE_3	.100	.140	.173	.195	.097	.171	.188	.399	.547	.530[a]	.292	.316	.429	.413	.435	.429	.423
SL_1	.080	.089	.036	.036	.067	.126	.155	.341	.433	.292	.625[a]	.713	.562	.416	.129	.128	.122
SL_2	.106	.106	.070	.083	.055	.116	.158	.338	.435	.316	.713	.833[a]	.623	.480	.173	.164	.164
SL_3	.090	.125	.092	.086	.134	.211	.221	.433	.559	.429	.562	.623	.599[a]	.454	.305	.309	.294
SL_4	.140	.156	.206	.231	.040	.112	.144	.322	.457	.413	.416	.480	.454	.433[a]	.323	.309	.318
BI_1	.089	.149	.200	.213	.126	.221	.201	.193	.280	.435	.129	.173	.305	.323	.925[a]	.903	.894
BI_2	.097	.156	.189	.192	.154	.256	.224	.207	.288	.429	.128	.164	.309	.309	.903	.89[a]	.871
BI_3	.108	.163	.226	.241	.110	.194	.180	.187	.278	.423	.122	.164	.294	.318	.894	.871	.868[a]

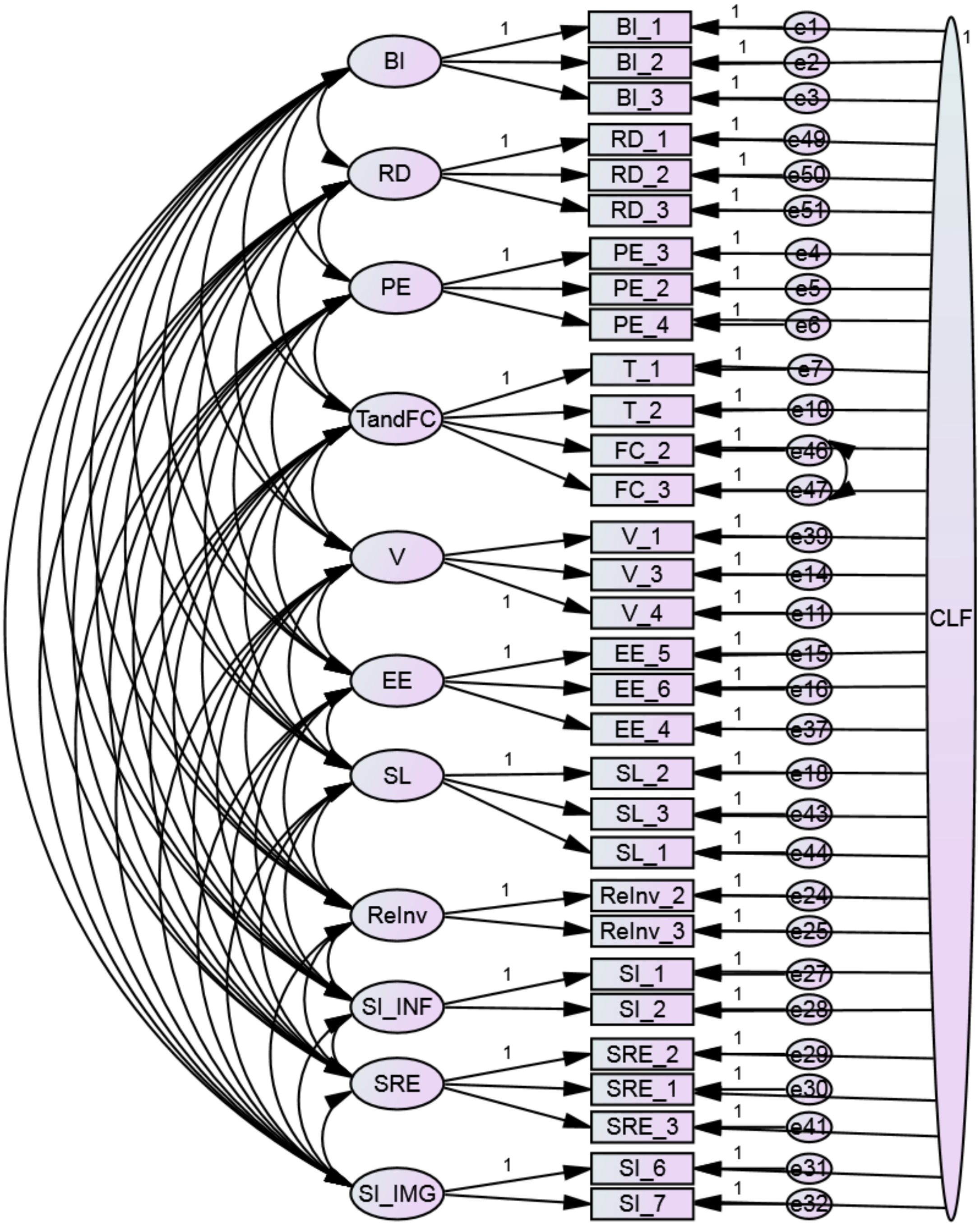
PE_2	PE_3	EE_2	EE_4	EE_5	EE_6	SI_1	SI_2	SI_3	SI_6	SI_7	FC_1	FC_2	FC_3	RD_1	RD_2	RD_3	V_1
	5.446E-6	-.002	.018	-.011	.014	-.017	.011	.038	-.010	.001	-.020	.007	-.015	.013	.011	-.013	-.008
5.446E-6		2.972E-5	-7.581E-5	3.566E-5	-4.520E-5	5.729E-5	-4.457E-5	-9.845E-5	2.746E-5	-3.168E-6	5.844E-5	-1.140E-5	2.423E-5	-4.212E-5	-2.216E-5	3.406E-5	-3.899E-7
-.002	2.972E-5		.194	-.008	-.041	.017	-.002	-.041	-.006	-.007	-.054	-.034	.094	-.033	-.007	.002	-.020
.018	-7.581E-5	.194		-.011	-.027	.005	-.014	.018	.014	-.007	.037	-.031	.089	.039	-.008	-.008	.024
-.011	3.566E-5	-.008	-.011		.008	.003	-.002	.003	-.005	.001	-.011	-.005	-.011	-.018	-.001	.005	-.004
.014	-4.520E-5	-.041	-.027	.008		-.008	.007	-.006	.007	.002	.017	.015	-.019	.023	.002	-.004	.003
-.017	5.729E-5	.017	.005	.003	-.008		.001	-.005	.001	.000	-.004	.006	.015	-.017	.004	-.003	.004
.011	-4.457E-5	-.002	-.014	-.002	.007	.001		.003	.002	-.001	-.007	-.024	-.018	.017	-.008	.005	-.004
.038	-9.845E-5	-.041	.018	.003	-.006	-.005	.003		-.031	.008	-.006	.075	-.017	-.014	-.004	.017	-.027
-.010	2.746E-5	-.006	.014	-.005	.007	.001	.002	-.031		-.001	.016	.003	-.021	.000	.012	-.016	.006
.001	-3.168E-6	-.007	-.007	.001	.002	.000	-.001	.008	-.001		-.003	-.005	.004	.001	-.002	.004	.000
-.020	5.844E-5	-.054	.037	-.011	.017	-.004	-.007	-.006	.016	-.003		.149	-.017	.022	.004	.001	.010
.007	-1.140E-5	-.034	-.031	-.005	.015	.006	-.024	.075	.003	-.005	.149		.069	.004	.010	.002	.004
-.015	2.423E-5	.094	.089	-.011	-.019	.015	-.018	-.017	-.021	.004	-.017	.069		.013	-.006	.000	.003
.013	-4.212E-5	-.033	.039	-.018	.023	-.017	.017	-.014	.000	.001	.022	.004	.013		.013	-.029	.060
.011	-2.216E-5	-.007	-.008	-.001	.002	.004	-.008	-.004	.012	-.002	.004	.010	-.006	.013		.004	.003
-.013	3.406E-5	.002	-.008	.005	-.004	-.003	.005	.017	-.016	.004	.001	.002	.000	-.029	.004		-.020
-.008	-3.899E-7	-.020	.024	-.004	.003	.004	-.004	-.027	.006	.000	.010	.004	.003	.060	.003	-.020	
-.006	1.833E-5	-.010	-.006	-.001	.004	.002	-.005	.000	-.006	.001	.015	.025	.003	-.006	-.004	.010	.016
.003	4.834E-6	-.003	.002	-.004	.007	-.006	.001	.040	.018	-.006	.025	.011	.007	-.017	.004	.003	-.016
.012	-2.594E-5	.005	-.046	.013	-.010	-.001	.013	-.029	.008	.006	-.062	-.047	-.028	-.028	-.003	.004	-.015
-.001	4.096E-6	-.017	-.002	.009	-.008	-.007	.017	-.007	-.007	-.002	-.057	-.066	-.020	.000	.001	-.007	-.015
.018	-5.094E-5	.031	.044	-.012	.003	.001	-.002	-.002	.014	-.004	.035	-.028	-.035	.020	.014	-.020	.008
-.010	2.718E-5	-.023	-.027	.004	.005	-.007	.005	.013	-.009	.002	.007	.010	.003	.001	-.002	.005	-.008
.011	-2.693E-5	.007	.020	-.004	.001	.006	-.008	-.022	.012	.000	-.004	.020	.006	-.011	.001	-.002	.042
-.012	3.097E-5	.012	-.006	.006	-.013	.013	-.021	.023	-.013	.005	-.003	.040	-.027	.001	.006	.000	-.003
.010	-1.349E-5	.011	-.014	.001	1.751E-5	.003	.001	-.010	.002	-.001	-.030	-.026	.011	-.025	.006	-.003	-.018
-.026	4.748E-5	-.018	.042	.000	-.002	-.018	.025	-.020	.010	-.001	-.035	-.026	.005	.061	-.027	.008	.009
.009	-3.351E-5	-.018	.030	-.003	-.001	-.005	4.466E-5	.036	-.005	-9.908E-5	.020	.024	.006	-.006	.000	.001	.009
-.003	1.440E-5	-.012	-.008	-6.986E-5	.004	.001	-.001	-.008	.002	.001	-.014	.004	.001	.003	.004	-.003	-.007
-.003	-9.354E-6	.033	-.002	.004	-.010	-8.927E-5	.004	-.008	.016	-.003	.049	-.028	-.010	.010	-.003	-.005	.009
-.016	4.574E-5	.023	-.028	.004	.001	.001	.004	-.013	-.035	.004	.010	-.017	-.022	-.018	-.022	.031	.027
-.006	2.612E-5	-.009	-.002	.001	-7.352E-6	.001	-.003	-.003	.006	-.001	.014	.005	.001	-.005	.003	-.001	.006
.013	-3.860E-5	-.015	-.008	.002	.001	.003	-.003	.017	-.004	-.001	-.021	-.010	.003	.001	-.001	.001	-.013
-5.924E-5	-9.967E-6	.026	.004	-.003	.001	-.005	.006	-.008	-.007	.002	.005	.009	-.007	.004	-.003	.002	.003

V_3	V_4	T_1	T_2	ReInv_1	ReInv_2	ReInv_3	SRE_1	SRE_2	SRE_3	SL_1	SL_2	SL_3	SL_4	BI_1	BI_2	BI_3
-.006	.003	.012	-.001	.018	-.010	.011	-.012	.010	-.026	.009	-.003	-.003	-.016	-.006	.013	-5.924E-5
1.833E-5	4.834E-6	-2.594E-5	4.096E-6	-5.094E-5	2.718E-5	-2.693E-5	3.097E-5	-1.349E-5	4.748E-5	-3.351E-5	1.440E-5	-9.354E-6	4.574E-5	2.612E-5	-3.860E-5	-9.967E-6
-.010	-.003	.005	-.017	.031	-.023	.007	.012	.011	-.018	-.018	-.012	.033	.023	-.009	-.015	.026
-.006	.002	-.046	-.002	.044	-.027	.020	-.006	-.014	.042	.030	-.008	-.002	-.028	-.002	-.008	.004
-.001	-.004	.013	.009	-.012	.004	-.004	.006	.001	.000	-.003	-6.986E-5	.004	.004	.001	.002	-.003
.004	.007	-.010	-.008	.003	.005	.001	-.013	1.751E-5	-.002	-.001	.004	-.010	.001	-7.352E-6	.001	.001
.002	-.006	-.001	-.007	.001	-.007	.006	.013	.003	-.018	-.005	.001	-8.927E-5	.001	.001	.003	-.005
-.005	.001	.013	.017	-.002	.005	-.008	-.021	.001	.025	4.466E-5	-.001	.004	.004	-.003	-.003	.006
.000	.040	-.029	-.007	-.002	.013	-.022	.023	-.010	-.020	.036	-.008	-.008	-.013	-.003	.017	-.008
-.006	.018	.008	-.007	.014	-.009	.012	-.013	.002	.010	-.005	.002	.016	-.035	.006	-.004	-.007
.001	-.006	.006	-.002	-.004	.002	.000	.005	-.001	-.001	-9.908E-5	.001	-.003	.004	-.001	-.001	.002
.015	.025	-.062	-.057	.035	.007	-.004	-.003	-.030	-.035	.020	-.014	.049	.010	.014	-.021	.005
.025	.011	-.047	-.066	-.028	.010	.020	.040	-.026	-.026	.024	.004	-.028	-.017	.005	-.010	.009
.003	.007	-.028	-.020	-.035	.003	.006	-.027	.011	.005	.006	.001	-.010	-.022	.001	.003	-.007
-.006	-.017	-.028	.000	.020	.001	-.011	.001	-.025	.061	-.006	.003	.010	-.018	-.005	.001	.004
-.004	.004	-.003	.001	.014	-.002	.001	.006	.006	-.027	.000	.004	-.003	-.022	.003	-.001	-.003
.010	.003	.004	-.007	-.020	.005	-.002	.000	-.003	.008	.001	-.003	-.005	.031	-.001	.001	.002
.016	-.016	-.015	-.015	.008	-.008	.042	-.003	-.018	.009	.009	-.007	.009	.027	.006	-.013	.003
	.008	-.013	-.013	-.012	.004	.002	-.005	-.001	.002	.004	.003	.005	-.031	.002	-.002	.001
.008		-.004	-.019	-.009	.009	-.022	.011	.000	-.040	-.005	-.004	.000	.041	-.004	.007	.003
-.013	-.004		.093	.013	.005	-.037	.013	.021	.005	-.024	.009	-.016	.001	-.006	.006	.001
-.013	-.019	.093		.016	-.017	.013	-.012	.010	.020	-.001	-.006	.001	.028	-.001	.007	-.009
-.012	-.009	.013	.016		.003	-.017	.046	.003	-.043	-.016	.003	-.003	-.012	.002	-.012	.009
.004	.009	.005	-.017	.003		.005	-.003	-.002	.004	-.002	.005	-.008	-.007	.004	.005	-.011
.002	-.022	-.037	.013	-.017	.005		-.018	-.006	.015	.027	-.012	.015	.002	-.014	.000	.022
-.005	.011	.013	-.012	.046	-.003	-.018		.008	.012	.049	.006	-.072	-.040	.009	-.005	-.005
-.001	.000	.021	.010	.003	-.002	-.006	.008		.003	-.012	-.002	.023	-.002	-6.071E-5	-.008	.008
.002	-.040	.005	.020	-.043	.004	.015	.012	.003		-.005	-.003	-.002	.014	-.009	.014	-.004
.004	-.005	-.024	-.001	-.016	-.002	.027	.049	-.012	-.005		.005	-.029	-.001	.013	-.005	-.014
.003	-.004	.009	-.006	.003	.005	-.012	.006	-.002	-.003	.005		.002	-.010	-.001	-.003	.006
.005	.000	-.016	.001	-.003	-.008	.015	-.072	.023	-.002	-.029	.002		.061	-.005	.009	-.005
-.031	.041	.001	.028	-.012	-.007	.002	-.040	-.002	.014	-.001	-.010	.061		-.016	.029	-.010
.002	-.004	-.006	-.001	.002	.004	-.014	.009	-6.071E-5	-.009	.013	-.001	-.005	-.016		5.533E-5	.001
-.002	.007	.006	.007	-.012	.005	.000	-.005	-.008	.014	-.005	-.003	.009	.029	5.533E-5		-.002
.001	.003	.001	-.009	.009	-.011	.022	-.005	.008	-.004	-.014	.006	-.005	-.010	.001	-.002	

Extraction Method: Maximum Likelihood.

a. Reproduced communalities
b. Residuals are computed between observed and reproduced correlations. There are 15 (2.0%) no redundant residuals with absolute values greater than 0.05.

Appendix 6: Common Method Bias Model



Appendix 7: Standardised Regression weights Comparison

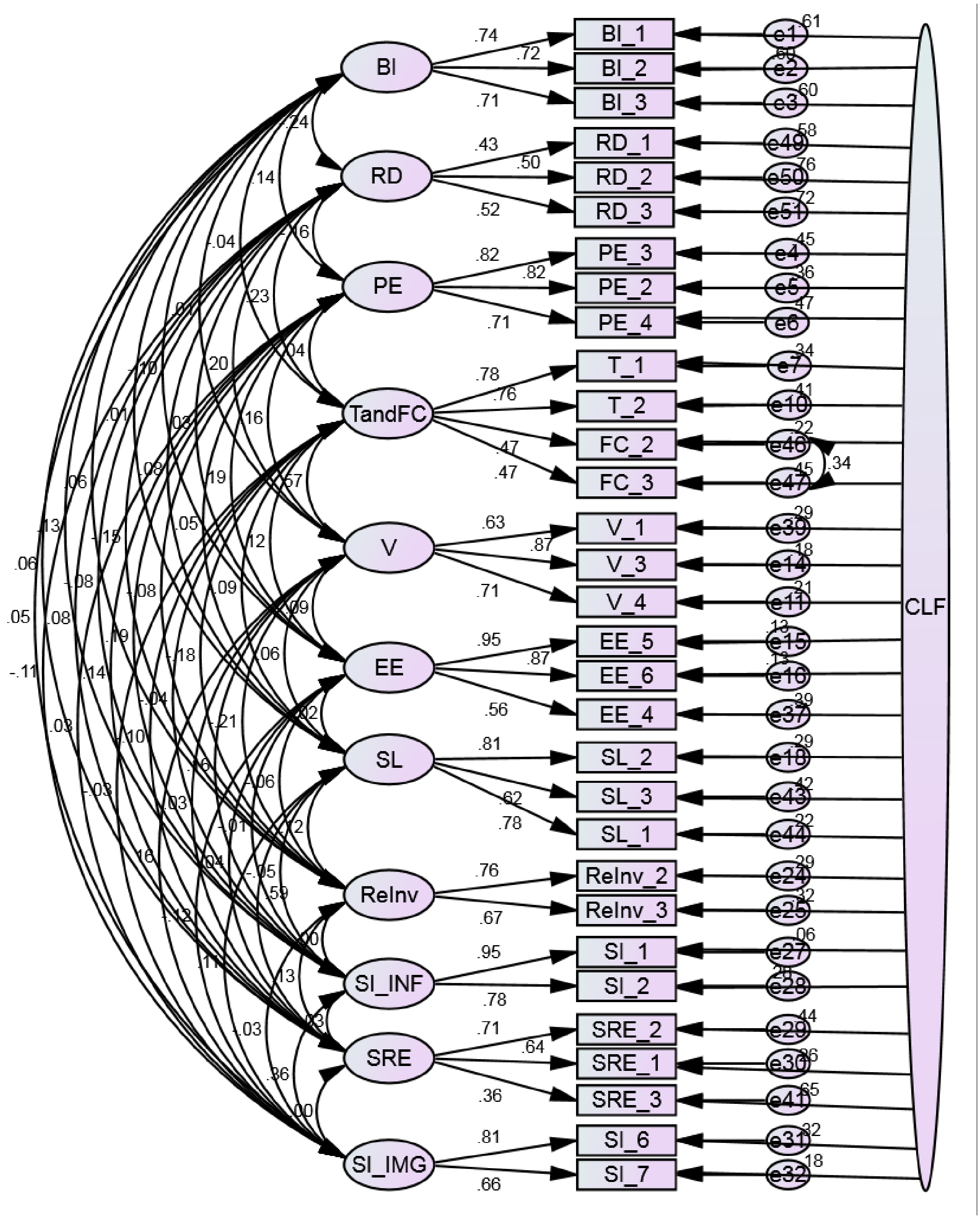
Comparing regression weights across models while highlighting differences larger than 0.2.

CFA Model with CLF				CFA Model without CLF				
			Estimate				Estimate	Delta
BI_1	<---	BI	0.834	BI_1	<---	BI	0.963	0.129
BI_2	<---	BI	0.811	BI_2	<---	BI	0.938	0.127
BI_3	<---	BI	0.791	BI_3	<---	BI	0.929	0.138
PE_3	<---	PE	0.814	PE_3	<---	PE	0.941	0.127
PE_2	<---	PE	0.798	PE_2	<---	PE	0.883	0.085
PE_4	<---	PE	0.699	PE_4	<---	PE	0.85	0.151
T_2	<---	TandFC	0.709	T_2	<---	TandFC	0.868	0.159
V_4	<---	V	0.678	V_4	<---	V	0.75	0.072
V_3	<---	V	0.823	V_3	<---	V	0.862	0.039
EE_5	<---	EE	0.958	EE_5	<---	EE	0.954	-0.004
EE_6	<---	EE	0.851	EE_6	<---	EE	0.891	0.04
SL_2	<---	SL	0.825	SL_2	<---	SL	0.861	0.036
ReInv_2	<---	ReInv	0.821	ReInv_2	<---	ReInv	0.775	-0.046
ReInv_3	<---	ReInv	0.714	ReInv_3	<---	ReInv	0.778	0.064
SI_2	<---	SI_INF	0.742	SI_2	<---	SI_INF	0.95	0.208
SI_1	<---	SI_INF	0.985	SI_1	<---	SI_INF	0.802	-0.183
SRE_1	<---	SRE	0.613	SRE_1	<---	SRE	0.627	0.014
SRE_2	<---	SRE	0.727	SRE_2	<---	SRE	0.801	0.074
SI_7	<---	SI_IMG	0.649	SI_7	<---	SI_IMG	0.627	-0.022
SI_6	<---	SI_IMG	0.857	SI_6	<---	SI_IMG	0.941	0.084
T_1	<---	TandFC	0.765	T_1	<---	TandFC	0.84	0.075
EE_4	<---	EE	0.534	EE_4	<---	EE	0.614	0.08
V_1	<---	V	0.579	V_1	<---	V	0.697	0.118

SRE_3	<---	SRE	0.4	SRE_3	<---	SRE	0.715	0.315
SL_3	<---	SL	0.648	SL_3	<---	SL	0.738	0.09
SL_1	<---	SL	0.786	SL_1	<---	SL	0.794	0.008
FC_2	<---	TandFC	0.408	FC_2	<---	TandFC	0.525	0.117
FC_3	<---	TandFC	0.416	FC_3	<---	TandFC	0.636	0.22
RD_1	<---	RD	0.021	RD_1	<---	RD	0.668	0.647
RD_2	<---	RD	-0.566	RD_2	<---	RD	0.946	1.512
								1.395
RD_3	<---	RD	-0.517	RD_3	<---	RD	0.878	

Appendix 8: Common Method Bias Adjusted Model

The following is the original model with the common latent factor added.



Reliability & Validity

	CR	AVE	MSV	ASV	SI_IMG	BI	PE	TandFC	V	EE	SL	RelInv	SI_INF	SRE	RD
SI_IMG	0.703	0.544	0.130	0.020	**0.738**										
BI	0.768	0.524	0.057	0.012	0.049	**0.724**									
PE	0.827	0.615	0.038	0.017	0.033	0.143	**0.784**								
TandFC	0.724	0.410	0.328	0.046	-0.031	-0.040	0.037	**0.640**							
V	0.783	0.551	0.328	0.050	0.165	0.014	0.157	0.573	**0.742**						
EE	0.849	0.662	0.038	0.009	-0.123	-0.104	0.194	0.124	0.089	**0.814**					
SL	0.784	0.550	0.346	0.039	0.112	0.005	0.045	-0.094	0.055	-0.023	**0.742**				
RelInv	0.680	0.516	0.046	0.015	-0.033	0.064	-0.083	-0.182	-0.214	-0.058	0.117	**0.719**			
SI_INF	0.862	0.760	0.130	0.022	0.360	0.128	0.188	-0.043	0.156	-0.014	-0.049	0.002	**0.872**		
SRE	0.601	0.349	0.346	0.041	-0.003	0.056	0.141	-0.102	0.031	-0.041	0.588	0.131	0.030	**0.591**	

RD	0.482	0.238	0.057	0.023	-0.110	-0.239	-0.157	0.234	0.195	0.033	0.076	-0.146	-0.082	0.076	**0.488**

VALIDITY CONCERNS

Convergent Validity: the AVE for TandFC is less than 0.50.

Reliability: the CR for ReInv is less than 0.70.

Reliability: the CR for SRE is less than 0.70.

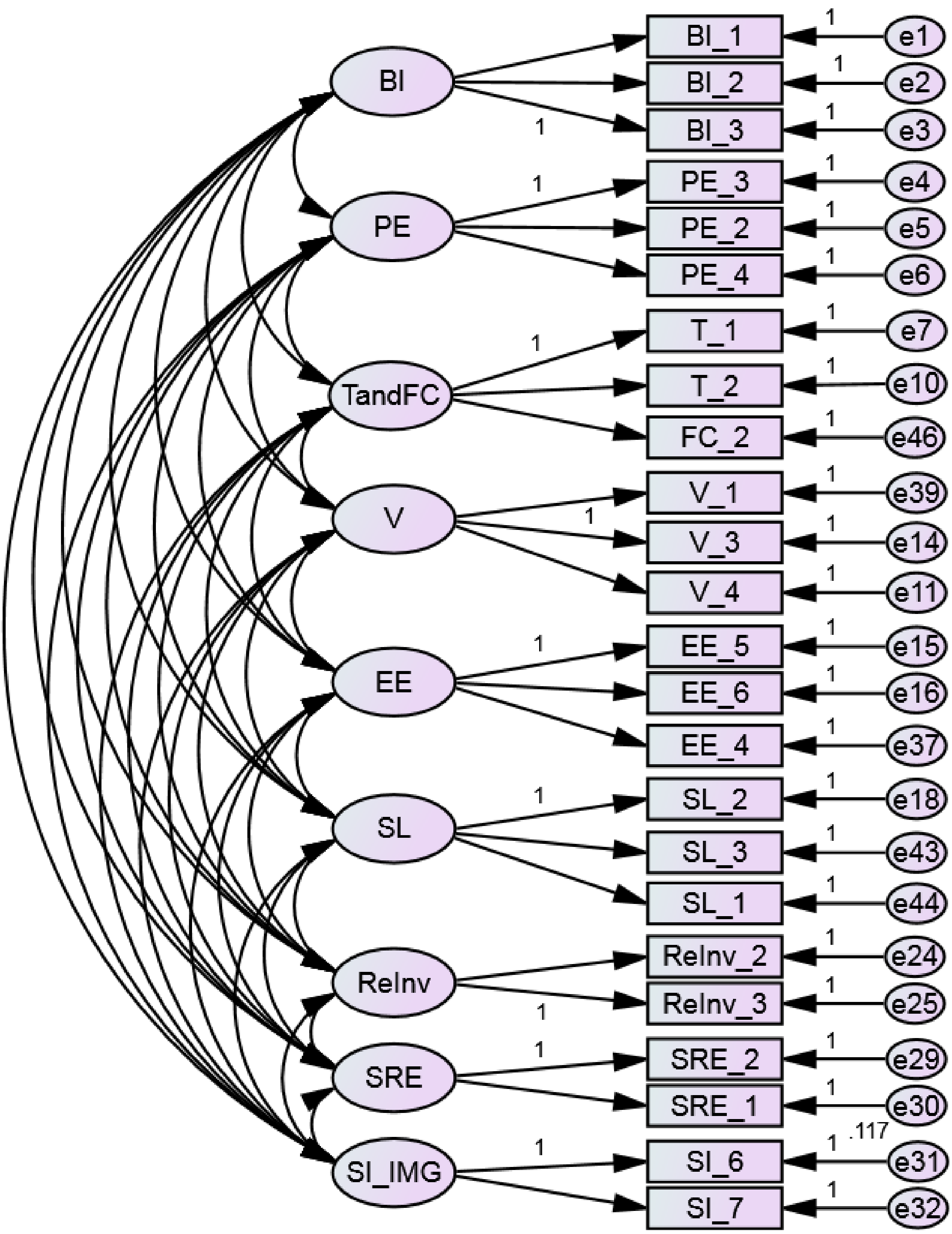
Convergent Validity: the AVE for SRE is less than 0.50.

Reliability: the CR for RD is less than 0.70.

Convergent Validity: the AVE for RD is less than 0.50.

Appendix 9: Final Model without CLF

The following is the original model without the affected items.



Reliability & Validity

	CR	AVE	MSV	ASV	SRE	BI	PE	TandFC	V	EE	SL	RelInv	SI_IMG
SRE	0.733	0.584	0.442	0.104	**0.764**								
BI	0.960	0.890	0.160	0.072	0.338	**0.943**							
PE	0.921	0.795	0.160	0.068	0.329	0.400	**0.892**						
TandFC	0.800	0.582	0.387	0.073	0.153	0.249	0.240	**0.763**					
V	0.815	0.597	0.387	0.077	0.161	0.185	0.261	0.622	**0.772**				
EE	0.868	0.693	0.059	0.013	0.045	0.023	0.242	0.162	0.127	**0.832**			
SL	0.841	0.638	0.442	0.086	0.665	0.244	0.211	0.084	0.146	0.038	**0.799**		
RelInv	0.752	0.603	0.095	0.035	0.309	0.289	0.124	0.018	-0.089	0.007	0.253	**0.777**	
SI_IMG	0.781	0.652	0.063	0.031	0.145	0.250	0.167	0.133	0.227	-0.051	0.221	0.121	**0.808**

No Validity Concerns

Appendix 10: Assessment of Normality

Model 1 (Original Model)

Variable	min	max	skew	c.r.	kurtosis	c.r.
FC_2	1.000	7.000	-.646	-5.883	-.332	-1.509
SL_1	1.000	7.000	-1.125	-10.241	2.268	10.319
SL_3	1.000	7.000	-1.389	-12.643	3.701	16.844
V_1	1.000	7.000	-.850	-7.739	-.051	-.230
EE_4	1.000	7.000	-.633	-5.764	.189	.861
SI_7	1.000	7.000	-.164	-1.496	-.374	-1.702
SI_6	1.000	7.000	-.551	-5.011	.288	1.313
SRE_1	1.000	7.000	-1.632	-14.856	4.719	21.475
SRE_2	1.000	7.000	-1.634	-14.876	4.883	22.219
ReInv_3	2.000	7.000	-.595	-5.417	-.100	-.453
ReInv_2	2.000	7.000	-1.056	-9.607	1.818	8.274
SL_2	1.000	7.000	-1.323	-12.042	2.788	12.686
EE_6	1.000	7.000	.140	1.274	-.990	-4.507
EE_5	1.000	7.000	-.006	-.053	-1.017	-4.626
V_3	1.000	7.000	-.089	-.814	-.775	-3.528
V_4	1.000	7.000	-.380	-3.457	-.593	-2.700
T_2	1.000	7.000	-.261	-2.376	-.797	-3.628
T_1	1.000	7.000	-.181	-1.644	-.820	-3.732
PE_4	1.000	7.000	-.525	-4.782	-.269	-1.225
PE_2	1.000	7.000	-.435	-3.961	-.370	-1.685
PE_3	1.000	7.000	-.432	-3.932	-.251	-1.140
BI_3	1.000	7.000	-1.095	-9.969	1.034	4.707

BI_2	1.000	7.000	-1.335	-12.154	2.313	10.528
BI_1	1.000	7.000	-1.071	-9.747	1.078	4.906
Multivariate					159.866	50.443

Model 2 (Post-Hoc Model)

Variable	min	max	skew	c.r.	kurtosis	c.r.
FC_2	1.000	7.000	-.697	-6.132	-.222	-.975
V_1	1.000	7.000	-.857	-7.533	-.001	-.007
SI_7	1.000	7.000	-.159	-1.401	-.348	-1.530
SI_6	1.000	7.000	-.506	-4.451	.240	1.055
SRE_1	2.000	7.000	-.847	-7.451	1.039	4.567
SRE_2	3.000	7.000	-.712	-6.266	.752	3.306
ReInv_3	2.000	7.000	-.621	-5.463	-.025	-.112
ReInv_2	2.000	7.000	-.821	-7.216	.911	4.006
EE_6	1.000	7.000	.151	1.326	-.976	-4.292
EE_5	1.000	7.000	.015	.130	-1.011	-4.444
V_3	1.000	7.000	-.095	-.834	-.756	-3.323
V_4	1.000	7.000	-.383	-3.366	-.532	-2.337
T_2	1.000	7.000	-.282	-2.481	-.794	-3.493
T_1	1.000	7.000	-.211	-1.858	-.792	-3.481
PE_4	1.000	7.000	-.526	-4.627	-.246	-1.083
PE_2	1.000	7.000	-.397	-3.493	-.427	-1.879
PE_3	1.000	7.000	-.409	-3.597	-.262	-1.153
BI_3	1.000	7.000	-1.082	-9.517	1.094	4.810

BI_2	1.000	7.000	-1.346	-11.833	2.311	10.163
BI_1	1.000	7.000	-1.103	-9.696	1.242	5.462
Multivariate					59.507	21.605

Appendix 11: Correlations and Covariances for the Original Model

Correlations

			Estimate
PE	<-->	TandFC	.240
PE	<-->	V	.261
PE	<-->	EE	.243
PE	<-->	SL	.210
PE	<-->	ReInv	.124
PE	<-->	SRE	.329
PE	<-->	SI_IMG	.160
TandFC	<-->	V	.622
TandFC	<-->	EE	.162
TandFC	<-->	SL	.084
TandFC	<-->	ReInv	.019
TandFC	<-->	SRE	.153
TandFC	<-->	SI_IMG	.129
V	<-->	EE	.127
V	<-->	SL	.146
V	<-->	ReInv	-.089
V	<-->	SRE	.161
V	<-->	SI_IMG	.220
EE	<-->	SL	.038
EE	<-->	ReInv	.007
EE	<-->	SRE	.045

EE	<-->	SI_IMG	-.049
SL	<-->	ReInv	.253
SL	<-->	SRE	.665
SL	<-->	SI_IMG	.216
ReInv	<-->	SRE	.309
ReInv	<-->	SI_IMG	.121
SRE	<-->	SI_IMG	.140

Covariances

			Estimate	S.E.	C.R.	P
PE	<-->	TandFC	.447	.096	4.649	***
PE	<-->	V	.445	.090	4.963	***
PE	<-->	EE	.517	.105	4.910	***
PE	<-->	SL	.245	.060	4.080	***
PE	<-->	ReInv	.140	.061	2.279	.023
PE	<-->	SRE	.372	.062	6.003	***
PE	<-->	SI_IMG	.285	.084	3.382	***
TandFC	<-->	V	1.039	.106	9.846	***
TandFC	<-->	EE	.338	.106	3.189	.001
TandFC	<-->	SL	.096	.060	1.601	.109
TandFC	<-->	ReInv	.020	.062	.331	.740
TandFC	<-->	SRE	.170	.061	2.780	.005
TandFC	<-->	SI_IMG	.225	.086	2.632	.008
V	<-->	EE	.243	.098	2.484	.013

V	<-->	SL	.153	.056	2.717	.007
V	<-->	ReInv	-.090	.058	-1.564	.118
V	<-->	SRE	.163	.057	2.874	.004
V	<-->	SI_IMG	.350	.081	4.338	***
EE	<-->	SL	.049	.066	.754	.451
EE	<-->	ReInv	.008	.067	.122	.903
EE	<-->	SRE	.057	.066	.859	.390
EE	<-->	SI_IMG	-.098	.093	-1.049	.294
SL	<-->	ReInv	.174	.041	4.212	***
SL	<-->	SRE	.461	.045	10.180	***
SL	<-->	SI_IMG	.234	.055	4.294	***
ReInv	<-->	SRE	.207	.043	4.861	***
ReInv	<-->	SI_IMG	.128	.056	2.289	.022
SRE	<-->	SI_IMG	.149	.054	2.739	.006

Appendix 12: Direct effects for the Original Model

Direct Effects (Model 1)

	SI_IMG	SRE	ReInv	SL	EE	V	TandFC	PE	BI
BI	.125	.215	.276	.001	-.056	-.016	.140	.253	.000
FC_2	.000	.000	.000	.000	.000	.000	.563	.000	.000
SL_1	.000	.000	.000	.890	.000	.000	.000	.000	.000
SL_3	.000	.000	.000	.853	.000	.000	.000	.000	.000
V_1	.000	.000	.000	.000	.000	.795	.000	.000	.000
EE_4	.000	.000	.000	.000	.494	.000	.000	.000	.000
SI_7	.649	.000	.000	.000	.000	.000	.000	.000	.000
SI_6	1.000	.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.804	.000	.000	.000	.000	.000	.000	.000
SRE_2	.000	1.000	.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	1.000	.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.893	.000	.000	.000	.000	.000	.000
SL_2	.000	.000	.000	1.000	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.000	.977	.000	.000	.000	.000
EE_5	.000	.000	.000	.000	1.000	.000	.000	.000	.000
V_3	.000	.000	.000	.000	.000	1.000	.000	.000	.000
V_4	.000	.000	.000	.000	.000	.885	.000	.000	.000
T_2	.000	.000	.000	.000	.000	.000	.943	.000	.000
T_1	.000	.000	.000	.000	.000	.000	1.000	.000	.000
PE_4	.000	.000	.000	.000	.000	.000	.000	.900	.000
PE_2	.000	.000	.000	.000	.000	.000	.000	.943	.000
PE_3	.000	.000	.000	.000	.000	.000	.000	1.000	.000

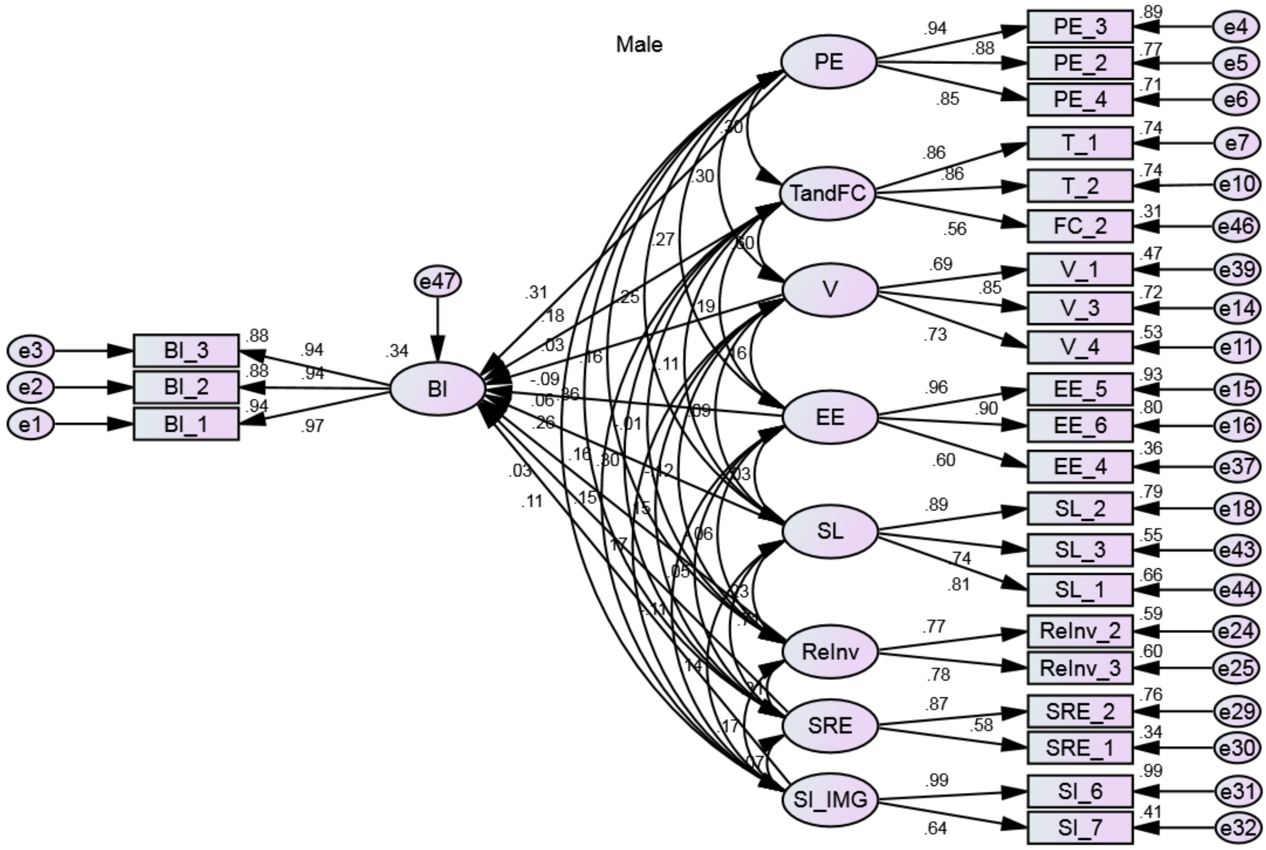
BI_3	.000	.000	.000	.000	.000	.000	.000	.000	1.000
BI_2	.000	.000	.000	.000	.000	.000	.000	.000	.925
BI_1	.000	.000	.000	.000	.000	.000	.000	.000	.994

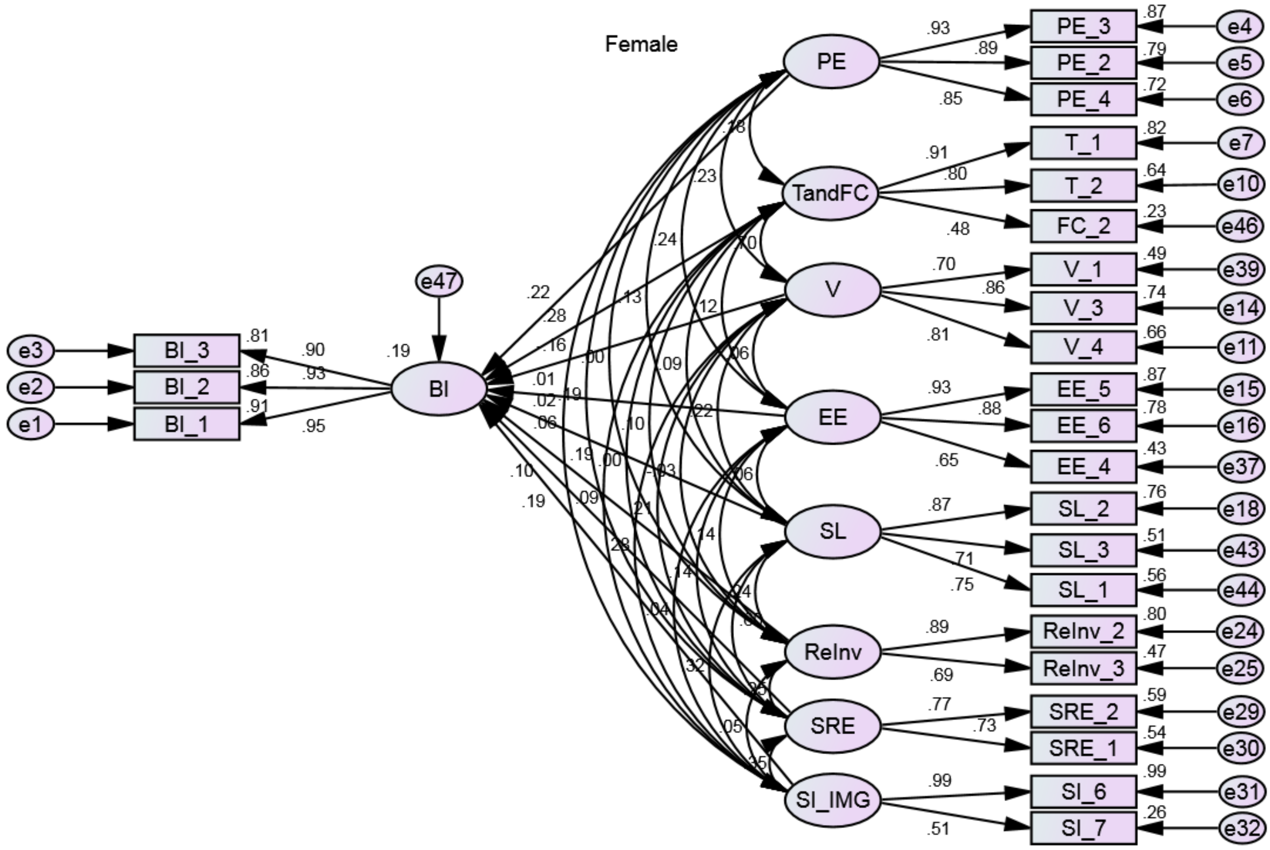
Standardised Direct Effects (Model 1)

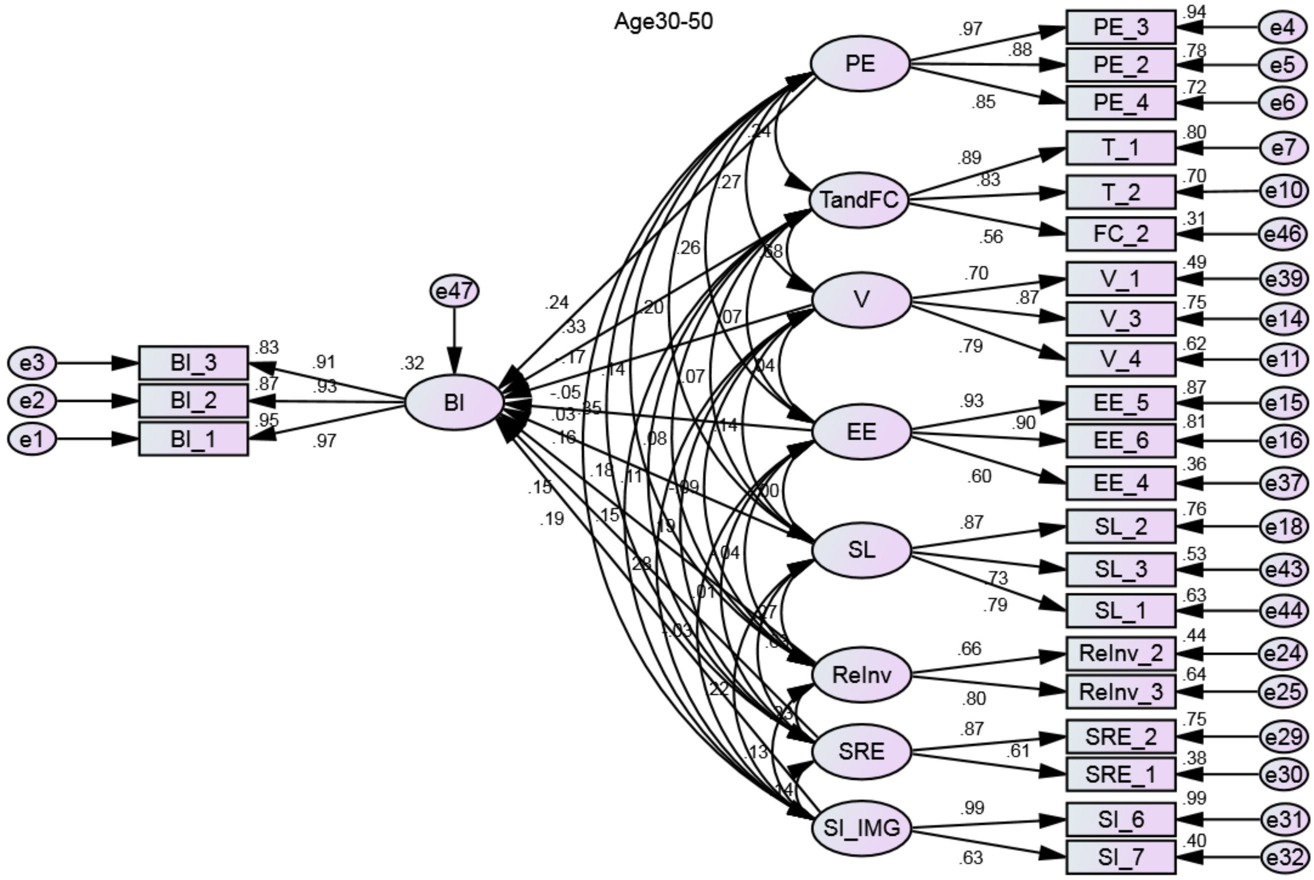
	SI_IMG	SRE	ReInv	SL	EE	V	TandFC	PE	BI
BI	.135	.147	.187	.001	-.072	-.016	.157	.291	.000
FC_2	.000	.000	.000	.000	.000	.000	.520	.000	.000
SL_1	.000	.000	.000	.794	.000	.000	.000	.000	.000
SL_3	.000	.000	.000	.742	.000	.000	.000	.000	.000
V_1	.000	.000	.000	.000	.000	.694	.000	.000	.000
EE_4	.000	.000	.000	.000	.612	.000	.000	.000	.000
SI_7	.594	.000	.000	.000	.000	.000	.000	.000	.000
SI_6	.994	.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.645	.000	.000	.000	.000	.000	.000	.000
SRE_2	.000	.868	.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	.773	.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.780	.000	.000	.000	.000	.000	.000
SL_2	.000	.000	.000	.857	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.000	.889	.000	.000	.000	.000
EE_5	.000	.000	.000	.000	.956	.000	.000	.000	.000
V_3	.000	.000	.000	.000	.000	.862	.000	.000	.000
V_4	.000	.000	.000	.000	.000	.752	.000	.000	.000
T_2	.000	.000	.000	.000	.000	.000	.839	.000	.000

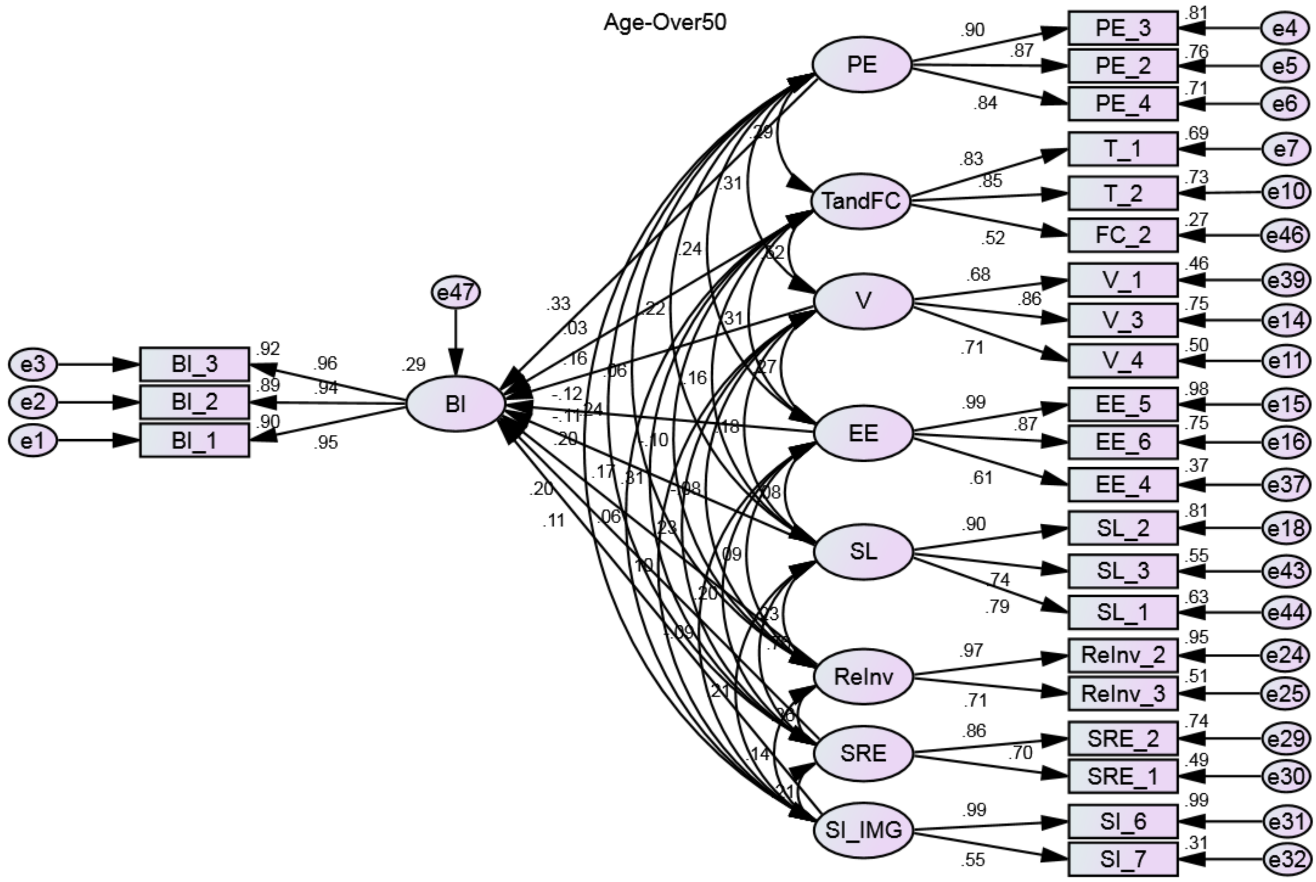
T_1	.000	.000	.000	.000	.000	.000	.879	.000	.000
PE_4	.000	.000	.000	.000	.000	.000	.000	.847	.000
PE_2	.000	.000	.000	.000	.000	.000	.000	.883	.000
PE_3	.000	.000	.000	.000	.000	.000	.000	.943	.000
BI_3	.000	.000	.000	.000	.000	.000	.000	.000	.929
BI_2	.000	.000	.000	.000	.000	.000	.000	.000	.937
BI_1	.000	.000	.000	.000	.000	.000	.000	.000	.964

Appendix 13: Moderated Models

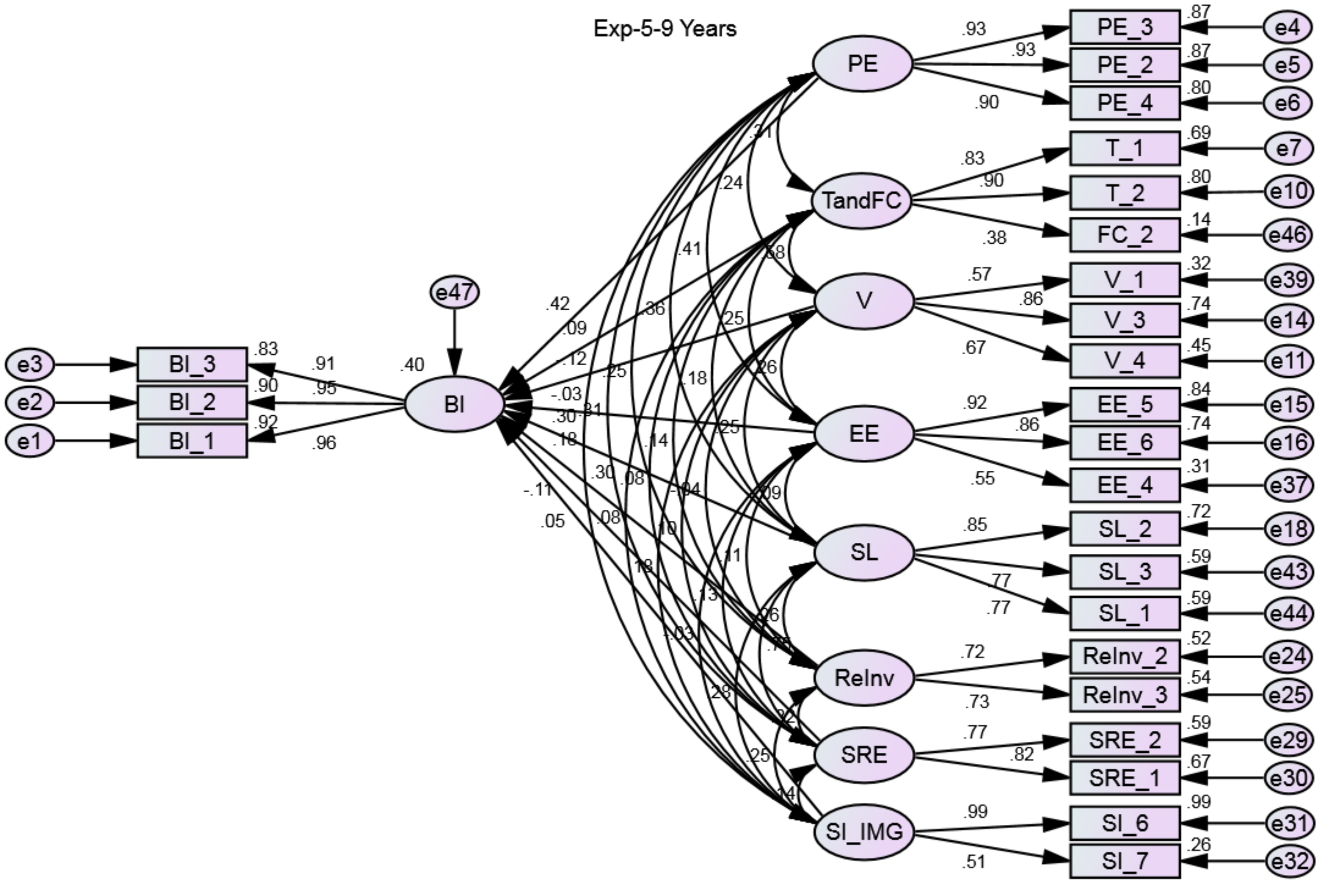



Female
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

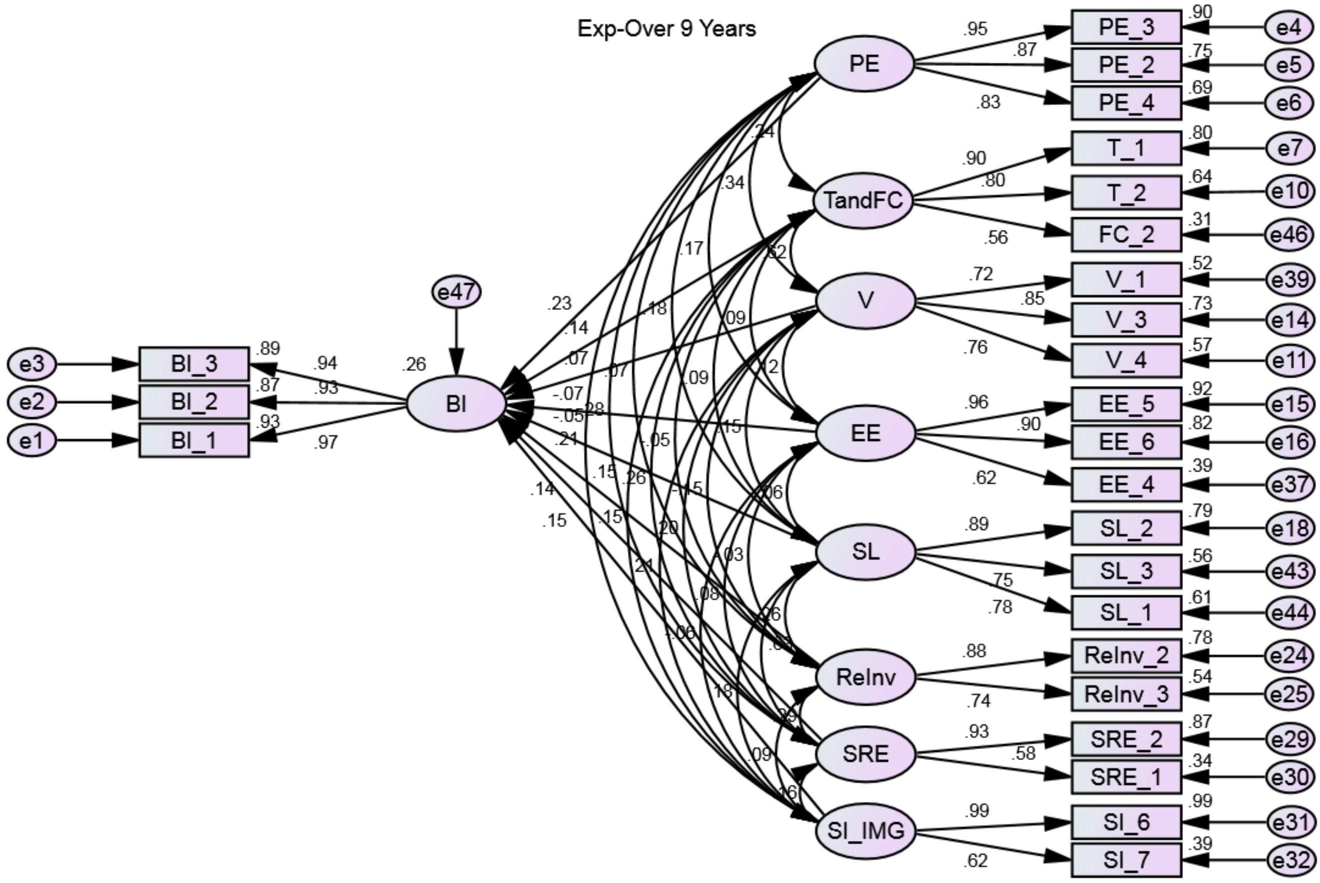

Age30-50
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

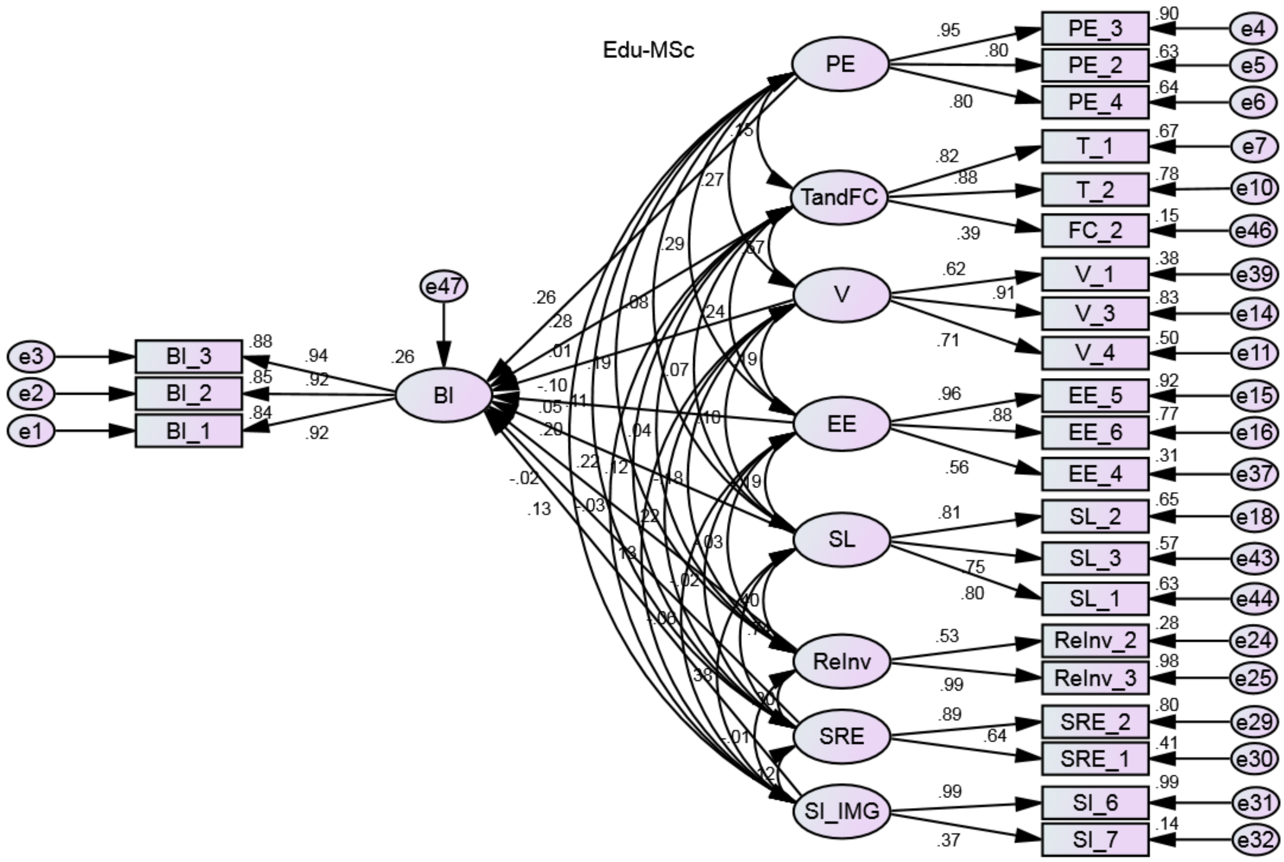


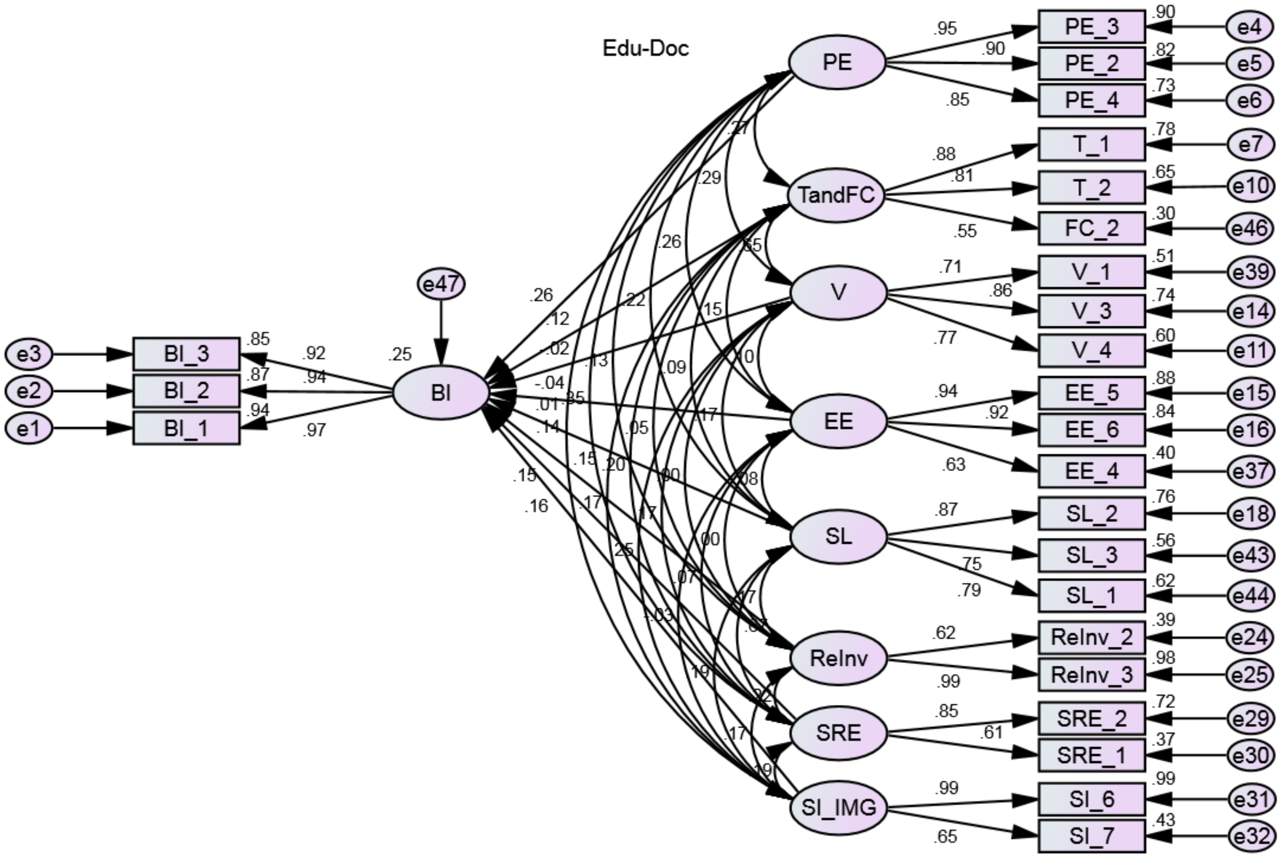
Age-Over50
PE
TandFC
V
EE
SL
ReInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
ReInv_2
ReInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

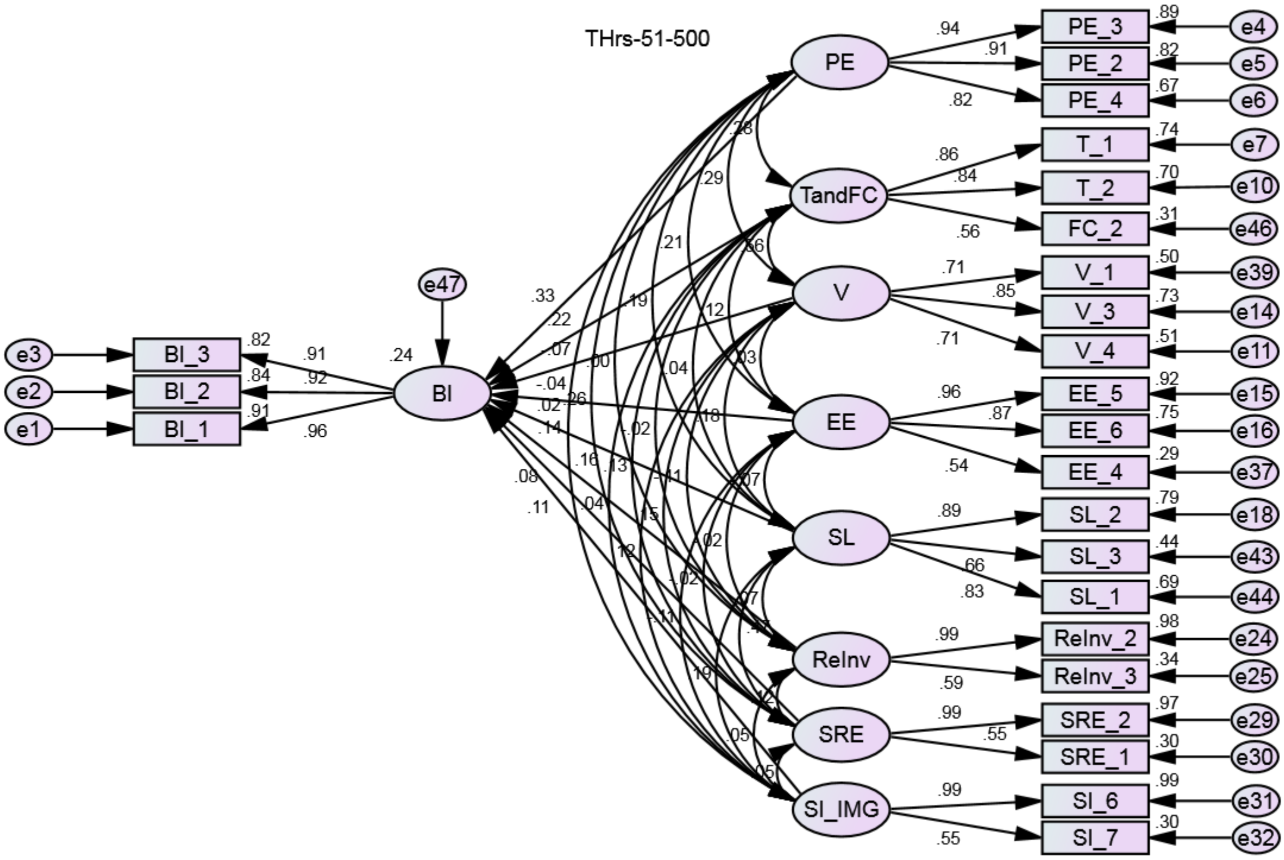


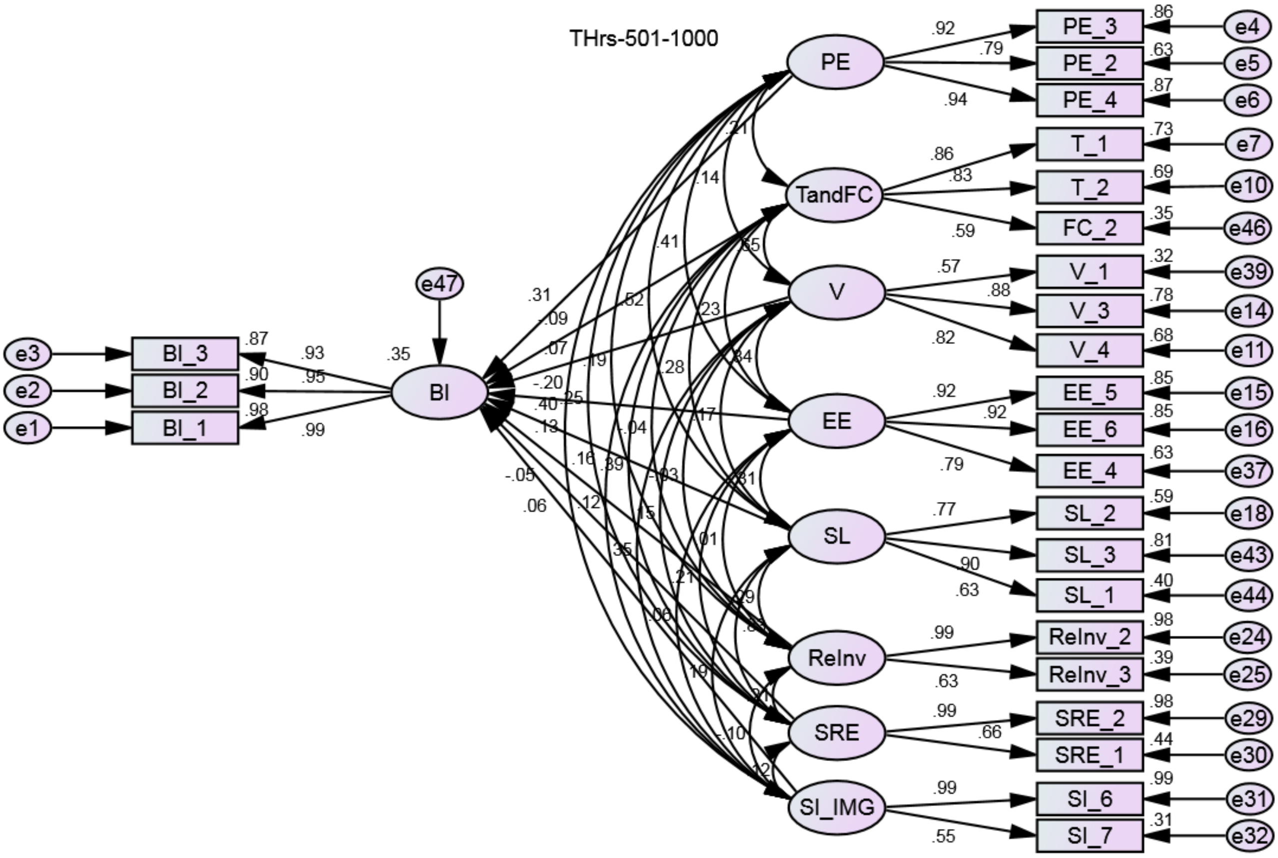
Exp-5-9 Years
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

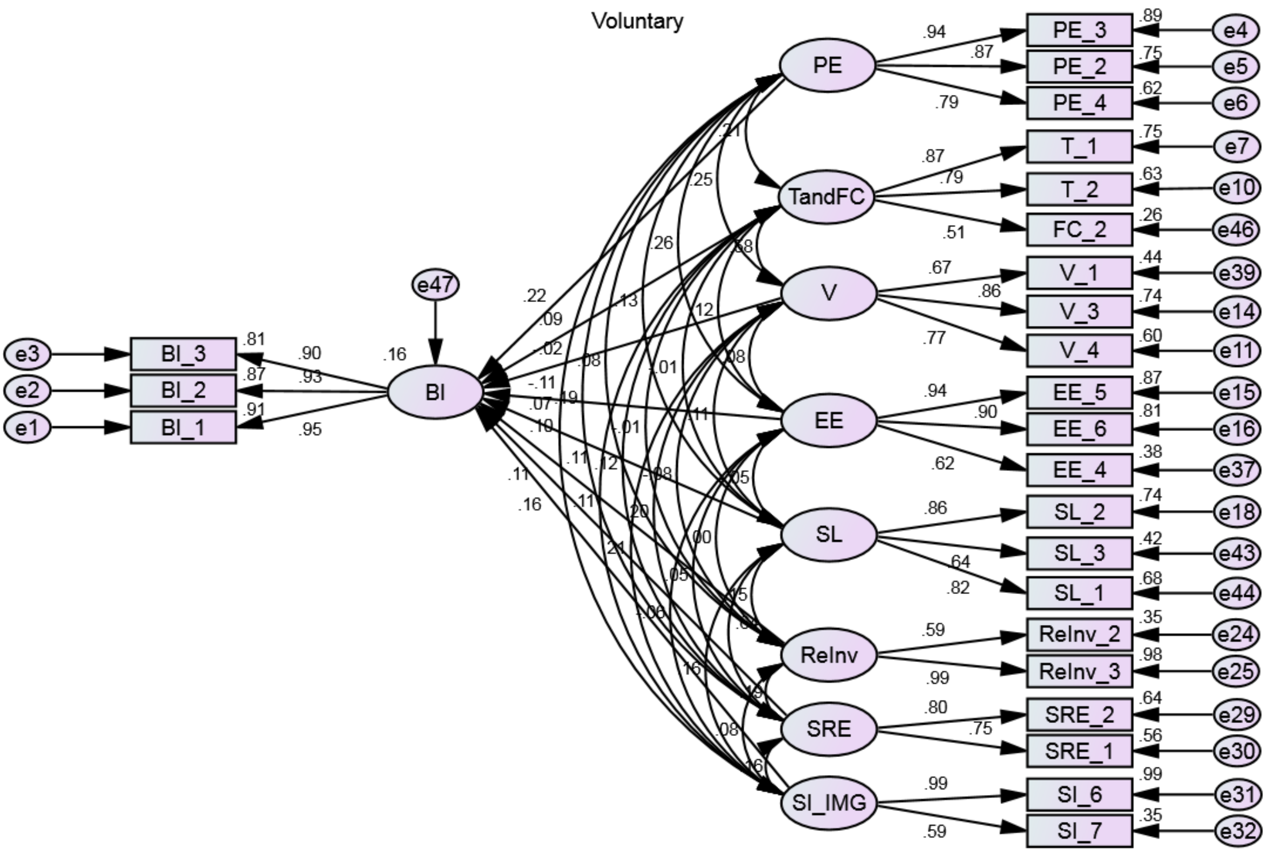

Exp-Over 9 Years
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e1
e2
e3
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32


Edu-MSc
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e1
e2
e3
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

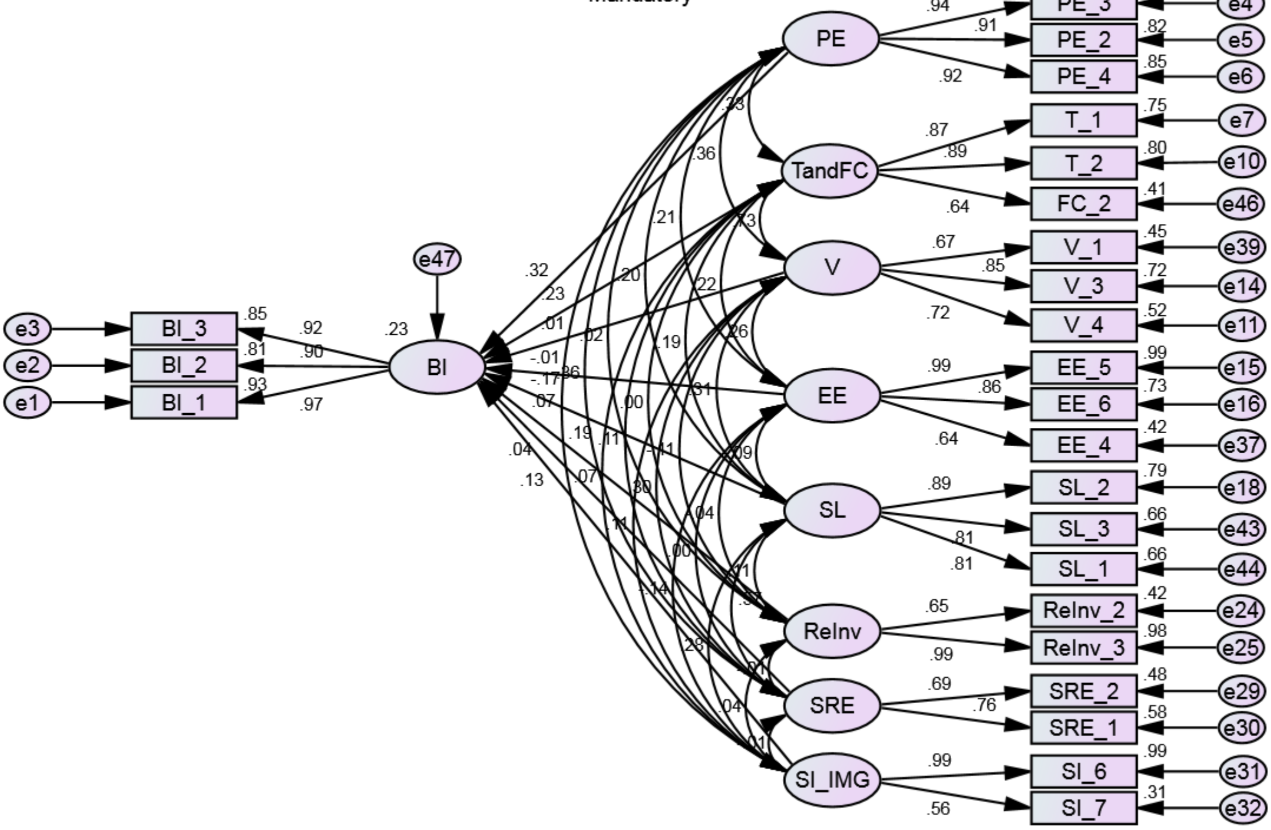

Edu-Doc
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32


THrs-51-500
PE
TandFC
V
EE
SL
RelInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
RelInv_2
RelInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

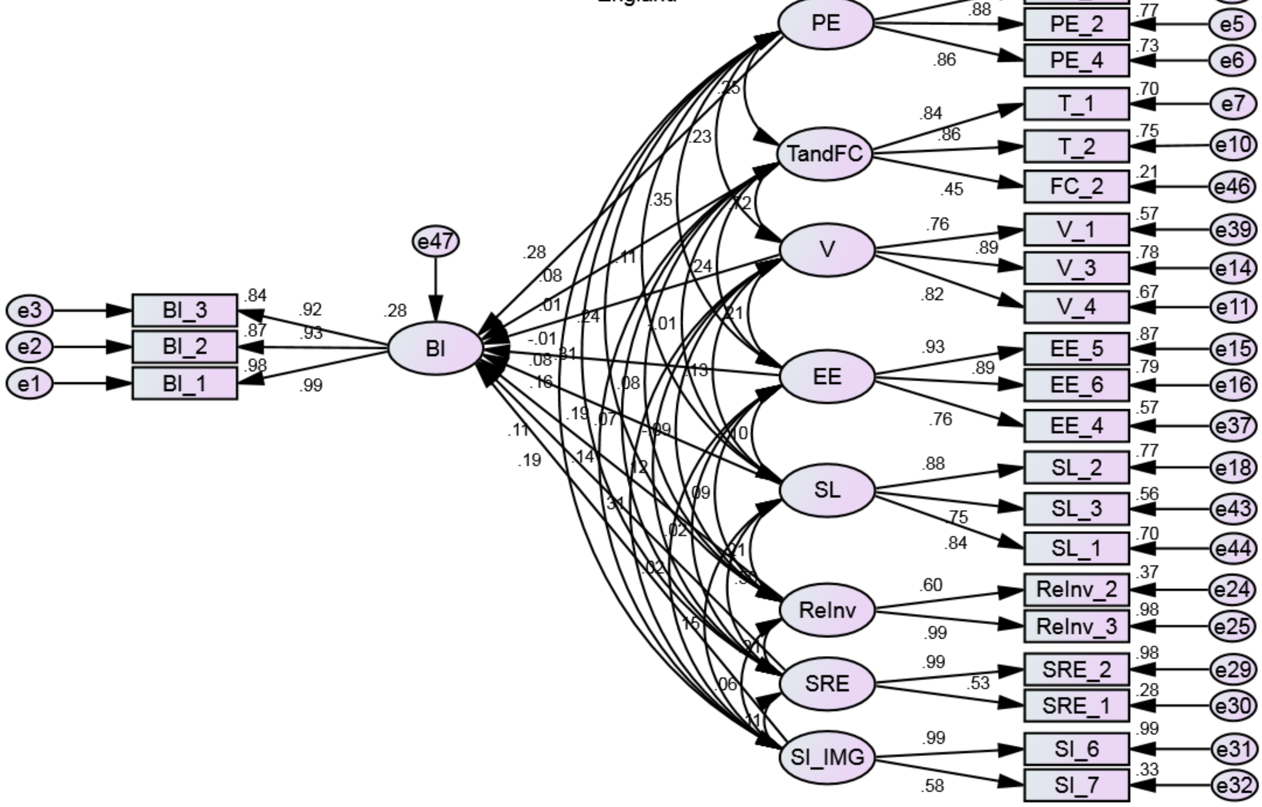

THrs-501-1000
PE
TandFC
V
EE
SL
ReInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
ReInv_2
ReInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

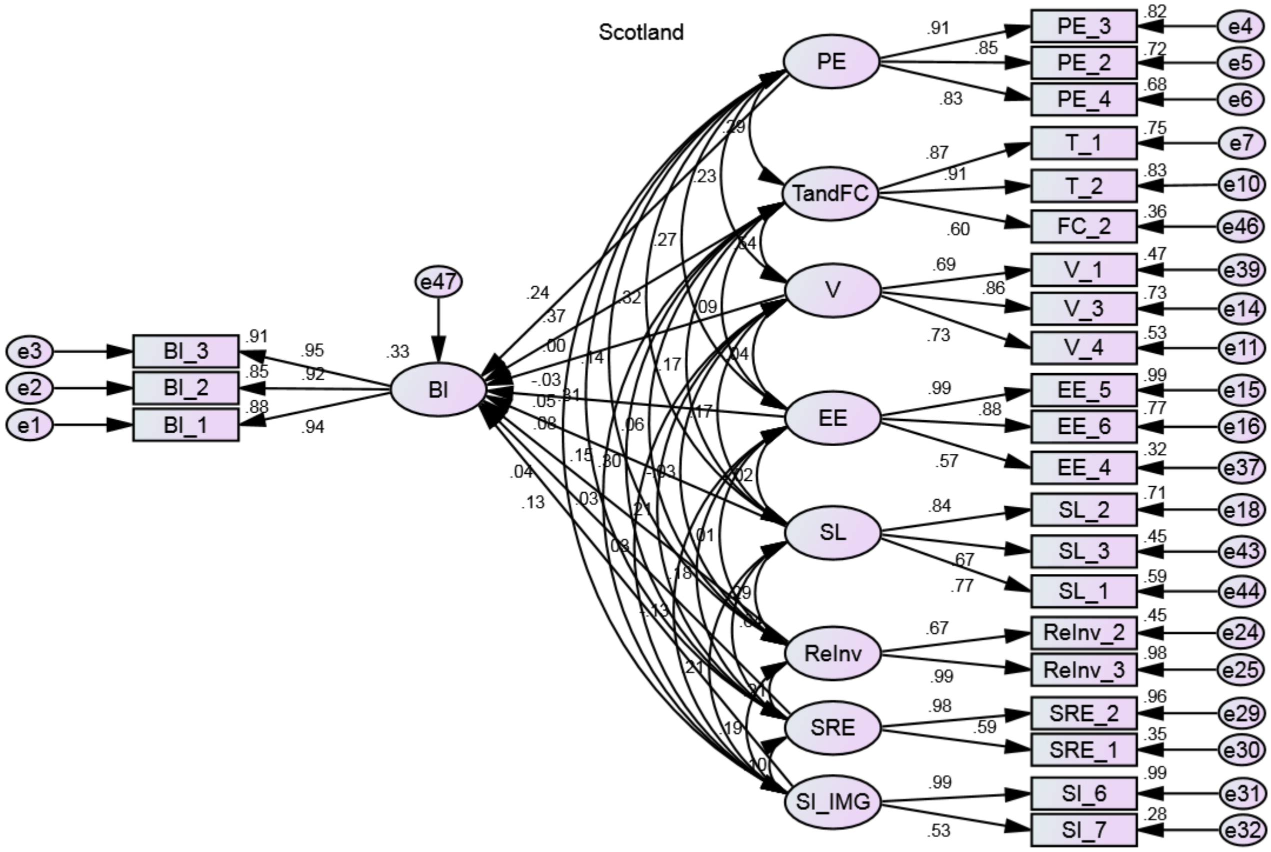

Voluntary
PE
TandFC
V
EE
SL
ReInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
ReInv_2
ReInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

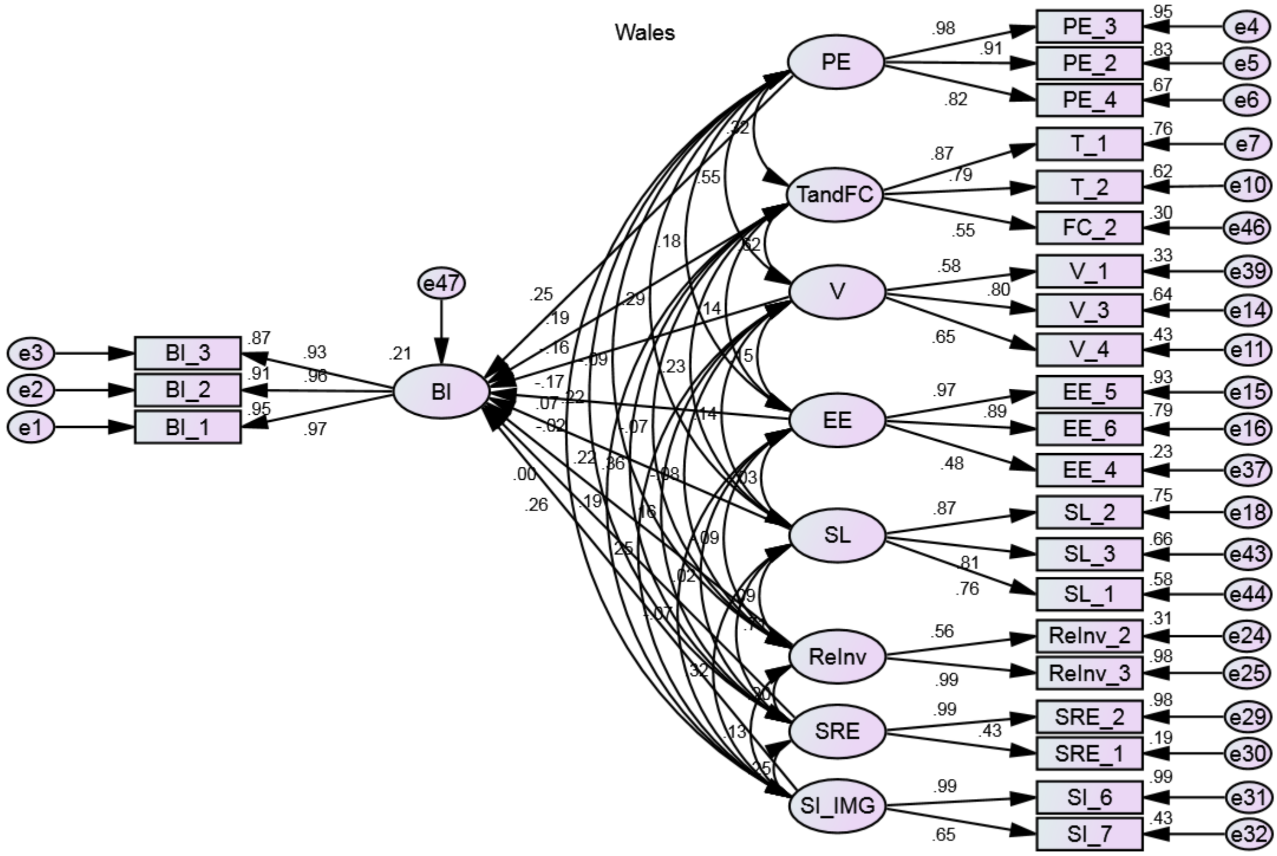
Mandatory



England




Scotland
PE
TandFC
V
EE
SL
ReInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
ReInv_2
ReInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32


Wales
PE
TandFC
V
EE
SL
ReInv
SRE
SI_IMG
BI
e47
BI_3
BI_2
BI_1
e3
e2
e1
PE_3
PE_2
PE_4
T_1
T_2
FC_2
V_1
V_3
V_4
EE_5
EE_6
EE_4
SL_2
SL_3
SL_1
ReInv_2
ReInv_3
SRE_2
SRE_1
SI_6
SI_7
e4
e5
e6
e7
e10
e46
e39
e14
e11
e15
e16
e37
e18
e43
e44
e24
e25
e29
e30
e31
e32

Appendix 14: Moderated Groups Z-Scores for differences

Major differences in the tables are highlighted. Rows highlighted in light green indicate the differences (z-score) are significant while rows highlighted in light grey show values worth discussing due to noticeable differences in the p-value or the estimates (i.e. strength of the effect). In all highlighted cases, at least one group must have a significant p-vaule < 0.05.

Gender

The moderated model had a CMIN/DF=1.654, p-value=.0, GFI=.896, CFI=.958, and RMSEA=.036 indicating a good fit (If not showing properly later use Initial moderation Group Differences v1 Hybrid Correct).

			Male		Female		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.283	0.000	0.170	0.003	-1.384
BI	<---	TandFC	0.177	0.023	0.199	0.035	0.184
BI	<---	V	0.036	0.656	-0.128	0.247	-1.197
BI	<---	EE	-0.075	0.095	0.007	0.898	1.205
BI	<---	SL	0.092	0.507	0.027	0.823	-0.352
BI	<---	ReInv	0.410	0.000	0.085	0.460	-2.046**
BI	<---	SRE	0.051	0.759	0.158	0.421	0.415
BI	<---	SI_IMG	0.109	0.041	0.157	0.013	0.583

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Age

The moderated model had a CMIN/DF=1.622, p-value=.0, GFI=.897, CFI=.960, and RMSEA=.036 indicating a good fit.

			30-50 Years		Over 50 Years		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.188	0.000	0.324	0.000	1.533
BI	<---	TandFC	0.263	0.000	0.028	0.793	-1.848*
BI	<---	V	-0.148	0.083	0.180	0.070	2.504**
BI	<---	EE	-0.035	0.396	-0.100	0.090	-0.902
BI	<---	SL	0.040	0.723	-0.162	0.404	-0.899
BI	<---	RelInv	0.215	0.027	0.342	0.012	0.759
BI	<---	SRE	0.223	0.094	0.329	0.213	0.359
BI	<---	SI_IMG	0.159	0.000	0.109	0.120	-0.588

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Experience

The moderated model had a CMIN/DF=1.676, p-value=.0, GFI=.882, CFI=.950, and RMSEA=.040 indicating a good fit.

			5-9 Years		Over 9 Years		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.330	0.000	0.208	0.000	-1.189
BI	<---	TandFC	0.079	0.491	0.130	0.078	0.378
BI	<---	V	-0.112	0.378	0.073	0.403	1.201
BI	<---	EE	-0.025	0.772	-0.057	0.171	-0.336
BI	<---	SL	0.400	0.112	-0.074	0.506	-1.721*

BI	<---	ReInv	0.262	0.136	0.338	0.000	0.378
BI	<---	SRE	-0.174	0.554	0.207	0.091	1.195
BI	<---	SI_IMG	0.046	0.626	0.148	0.004	0.945

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Education

The moderated model had a CMIN/DF=1.602, p-value=.0, GFI=.890, CFI=.958, and RMSEA=.036 indicating a good fit.

			Masters		Doctorate		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.209	0.027	0.227	0.000	0.169
BI	<---	TandFC	0.235	0.050	0.110	0.122	-0.895
BI	<---	V	0.006	0.960	-0.019	0.818	-0.173
BI	<---	EE	-0.069	0.344	-0.029	0.490	0.474
BI	<---	SL	0.066	0.822	0.022	0.857	-0.139
BI	<---	ReInv	0.198	0.101	0.168	0.006	-0.227
BI	<---	SRE	-0.029	0.918	0.222	0.122	0.793
BI	<---	SI_IMG	0.103	0.276	0.153	0.002	0.464

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Teaching Hours

The model had some negative error variances (e24 and e29). The variances were fixed to 0.02.

The resulting moderated model had a CMIN/DF=1.522, p-value=.0, GFI=.888, CFI=.958, and RMSEA=.035 indicating a good fit.

			51-500 Hours/Year		501-1000 Hours/Year		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.268	0.000	0.240	0.057	-0.204

BI	<---	TandFC	0.192	0.003	-0.072	0.623	-1.642
BI	<---	V	-0.068	0.342	0.051	0.703	0.785
BI	<---	EE	-0.033	0.429	-0.119	0.087	-1.065
BI	<---	SL	0.035	0.701	0.408	0.227	1.066
BI	<---	ReInv	0.266	0.008	0.170	0.213	-0.568
BI	<---	SRE	0.113	0.163	-0.041	0.873	-0.573
BI	<---	SI_IMG	0.098	0.045	0.044	0.609	-0.540

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Voluntary/Mandatory Adoption

The model had a negative error variance (e25). The variance was fixed to 0.02.

The moderated model had a CMIN/DF=1.475, p-value=.0, GFI=.897, CFI=.964, and RMSEA=.033 indicating a good fit.

			Voluntary		Mandatory		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.168	0.000	0.273	0.004	1.004
BI	<---	TandFC	0.069	0.259	0.210	0.159	0.878
BI	<---	V	-0.014	0.832	0.014	0.937	0.149
BI	<---	EE	-0.072	0.055	-0.006	0.936	0.813
BI	<---	SL	0.083	0.452	-0.219	0.225	-1.426
BI	<---	ReInv	0.098	0.069	0.080	0.403	-0.162
BI	<---	SRE	0.159	0.256	0.066	0.826	-0.279
BI	<---	SI_IMG	0.124	0.005	0.123	0.190	-0.012

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Country

The model had negative error variances (e25, e29). The variances were fixed to 0.02.

The moderated model had a CMIN/DF=1.633, p-value=.0, GFI=.841, CFI=.934, and RMSEA=.038 indicating a good fit.

			England		Scotland		Wales	
			Estimate	P	Estimate	P	Estimate	P
BI	<---	TandFC	0.079	0.543	0.321	0	0.146	0.236
BI	<---	RelInv	0.186	0.035	0.089	0.299	-0.023	0.817
BI	<---	SI_IMG	0.193	0.007	0.125	0.075	0.212	0.011

			England		Scotland		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.254	0	0.22	0.005	-0.306
BI	<---	TandFC	0.079	0.543	0.321	0	1.562
BI	<---	V	0.011	0.935	-0.005	0.962	-0.094
BI	<---	EE	-0.006	0.93	-0.022	0.696	-0.187
BI	<---	SL	0.111	0.384	0.067	0.697	-0.206
BI	<---	RelInv	0.186	0.035	0.089	0.299	-0.794
BI	<---	SRE	0.138	0.198	0.055	0.738	-0.423
BI	<---	SI_IMG	0.193	0.007	0.125	0.075	-0.682

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			England		Wales		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.254	0	0.194	0.047	-0.487
BI	<---	TandFC	0.079	0.543	0.146	0.236	0.377
BI	<---	V	0.011	0.935	-0.159	0.363	-0.772
BI	<---	EE	-0.006	0.93	-0.117	0.075	-1.202
BI	<---	SL	0.111	0.384	0.078	0.673	-0.147
BI	<---	ReInv	0.186	0.035	-0.023	0.817	-1.572
BI	<---	SRE	0.138	0.198	0.003	0.988	-0.656
BI	<---	SI_IMG	0.193	0.007	0.212	0.011	0.175

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			Scotland		Wales		
			Estimate	P	Estimate	P	z-score
BI	<---	PE	0.22	0.005	0.194	0.047	-0.211
BI	<---	TandFC	0.321	0	0.146	0.237	-1.162
BI	<---	V	-0.005	0.962	-0.159	0.363	-0.777
BI	<---	EE	-0.022	0.697	-0.117	0.075	-1.104
BI	<---	SL	0.067	0.698	0.078	0.673	0.045
BI	<---	ReInv	0.089	0.3	-0.023	0.817	-0.851
BI	<---	SRE	0.055	0.738	0.003	0.988	-0.217
BI	<---	SI_IMG	0.125	0.075	0.212	0.011	0.807

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1

Appendix 15: Correlations and Covariances for the Post-Hoc Model

Correlations

			Estimate
EE	<-->	RelInv	.034
EE	<-->	SRE	.095
EE	<-->	SI_IMG	-.115
RelInv	<-->	SRE	.380
RelInv	<-->	SI_IMG	.127
SRE	<-->	SI_IMG	.171

Covariances

			Estimate	S.E.	C.R.	P
EE	<-->	RelInv	.042	.068	.619	.536
EE	<-->	SRE	.112	.057	1.954	.051
EE	<-->	SI_IMG	-.220	.093	-2.372	.018
RelInv	<-->	SRE	.239	.039	6.142	***
RelInv	<-->	SI_IMG	.130	.055	2.346	.019
SRE	<-->	SI_IMG	.164	.046	3.557	***

Appendix 16: Total, Direct, and Indirect effects for the Post-Hoc Model

Total Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.191	.445	.000	.213	.000	.000	.000	.000
V	.179	.100	.000	.048	.226	.000	.000	.000
TandFC	.116	.065	.000	.031	.147	.650	.000	.000
BI	.219	.314	.259	.005	.262	.111	.171	.000
FC_2	.067	.037	.000	.018	.084	.373	.574	.000
V_1	.144	.081	.000	.039	.182	.807	.000	.000
SI_7	.678	.000	.000	.000	.000	.000	.000	.000
SI_6	1.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.660	.000	.000	.000	.000	.000	.000
SRE_2	.000	1.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	1.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.880	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.961	.000	.000	.000	.000
EE_5	.000	.000	.000	1.000	.000	.000	.000	.000
V_3	.179	.100	.000	.048	.226	1.000	.000	.000
V_4	.164	.092	.000	.044	.207	.916	.000	.000
T_2	.117	.066	.000	.031	.147	.654	1.006	.000
T_1	.116	.065	.000	.031	.147	.650	1.000	.000
PE_4	.175	.408	.000	.196	.917	.000	.000	.000
PE_2	.182	.423	.000	.203	.951	.000	.000	.000
PE_3	.191	.445	.000	.213	1.000	.000	.000	.000

BI_3	.219	.314	.259	.005	.262	.111	.171	1.000
BI_2	.209	.299	.247	.005	.250	.106	.163	.954
BI_1	.217	.310	.256	.005	.259	.110	.169	.989

Standardised Total Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.178	.256	.000	.243	.000	.000	.000	.000
V	.187	.065	.000	.062	.253	.000	.000	.000
TandFC	.112	.039	.000	.037	.151	.598	.000	.000
BI	.235	.207	.182	.007	.301	.114	.190	.000
FC_2	.059	.020	.000	.019	.080	.314	.525	.000
V_1	.132	.046	.000	.043	.178	.705	.000	.000
SI_7	.607	.000	.000	.000	.000	.000	.000	.000
SI_6	.994	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.586	.000	.000	.000	.000	.000	.000
SRE_2	.000	.989	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	.774	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.815	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.878	.000	.000	.000	.000
EE_5	.000	.000	.000	.964	.000	.000	.000	.000
V_3	.160	.055	.000	.053	.217	.858	.000	.000
V_4	.144	.050	.000	.047	.195	.770	.000	.000
T_2	.099	.034	.000	.033	.134	.529	.883	.000
T_1	.097	.033	.000	.032	.131	.518	.865	.000

PE_4	.153	.219	.000	.208	.856	.000	.000	.000
PE_2	.158	.226	.000	.216	.886	.000	.000	.000
PE_3	.168	.240	.000	.229	.940	.000	.000	.000
BI_3	.225	.198	.174	.007	.288	.109	.182	.955
BI_2	.223	.197	.173	.007	.286	.108	.181	.949
BI_1	.227	.200	.175	.007	.291	.110	.184	.965

Direct Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.191	.445	.000	.213	.000	.000	.000	.000
V	.136	.000	.000	.000	.226	.000	.000	.000
TandFC	.000	.000	.000	.000	.000	.650	.000	.000
BI	.154	.197	.259	-.050	.237	.000	.171	.000
FC_2	.000	.000	.000	.000	.000	.000	.574	.000
V_1	.000	.000	.000	.000	.000	.807	.000	.000
SI_7	.678	.000	.000	.000	.000	.000	.000	.000
SI_6	1.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.660	.000	.000	.000	.000	.000	.000
SRE_2	.000	1.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	1.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.880	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.961	.000	.000	.000	.000
EE_5	.000	.000	.000	1.000	.000	.000	.000	.000
V_3	.000	.000	.000	.000	.000	1.000	.000	.000

V_4	.000	.000	.000	.000	.000	.916	.000	.000
T_2	.000	.000	.000	.000	.000	.000	1.006	.000
T_1	.000	.000	.000	.000	.000	.000	1.000	.000
PE_4	.000	.000	.000	.000	.917	.000	.000	.000
PE_2	.000	.000	.000	.000	.951	.000	.000	.000
PE_3	.000	.000	.000	.000	1.000	.000	.000	.000
BI_3	.000	.000	.000	.000	.000	.000	.000	1.000
BI_2	.000	.000	.000	.000	.000	.000	.000	.954
BI_1	.000	.000	.000	.000	.000	.000	.000	.989

Standardised Direct Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.178	.256	.000	.243	.000	.000	.000	.000
V	.142	.000	.000	.000	.253	.000	.000	.000
TandFC	.000	.000	.000	.000	.000	.598	.000	.000
BI	.165	.130	.182	-.066	.273	.000	.190	.000
FC_2	.000	.000	.000	.000	.000	.000	.525	.000
V_1	.000	.000	.000	.000	.000	.705	.000	.000
SI_7	.607	.000	.000	.000	.000	.000	.000	.000
SI_6	.994	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.586	.000	.000	.000	.000	.000	.000
SRE_2	.000	.989	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	.774	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.815	.000	.000	.000	.000	.000

EE_6	.000	.000	.000	.878	.000	.000	.000	.000
EE_5	.000	.000	.000	.964	.000	.000	.000	.000
V_3	.000	.000	.000	.000	.000	.858	.000	.000
V_4	.000	.000	.000	.000	.000	.770	.000	.000
T_2	.000	.000	.000	.000	.000	.000	.883	.000
T_1	.000	.000	.000	.000	.000	.000	.865	.000
PE_4	.000	.000	.000	.000	.856	.000	.000	.000
PE_2	.000	.000	.000	.000	.886	.000	.000	.000
PE_3	.000	.000	.000	.000	.940	.000	.000	.000
BI_3	.000	.000	.000	.000	.000	.000	.000	.955
BI_2	.000	.000	.000	.000	.000	.000	.000	.949
BI_1	.000	.000	.000	.000	.000	.000	.000	.965

Indirect Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.000	.000	.000	.000	.000	.000	.000	.000
V	.043	.100	.000	.048	.000	.000	.000	.000
TandFC	.116	.065	.000	.031	.147	.000	.000	.000
BI	.065	.117	.000	.056	.025	.111	.000	.000
FC_2	.067	.037	.000	.018	.084	.373	.000	.000
V_1	.144	.081	.000	.039	.182	.000	.000	.000
SI_7	.000	.000	.000	.000	.000	.000	.000	.000
SI_6	.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.000	.000	.000	.000	.000	.000	.000

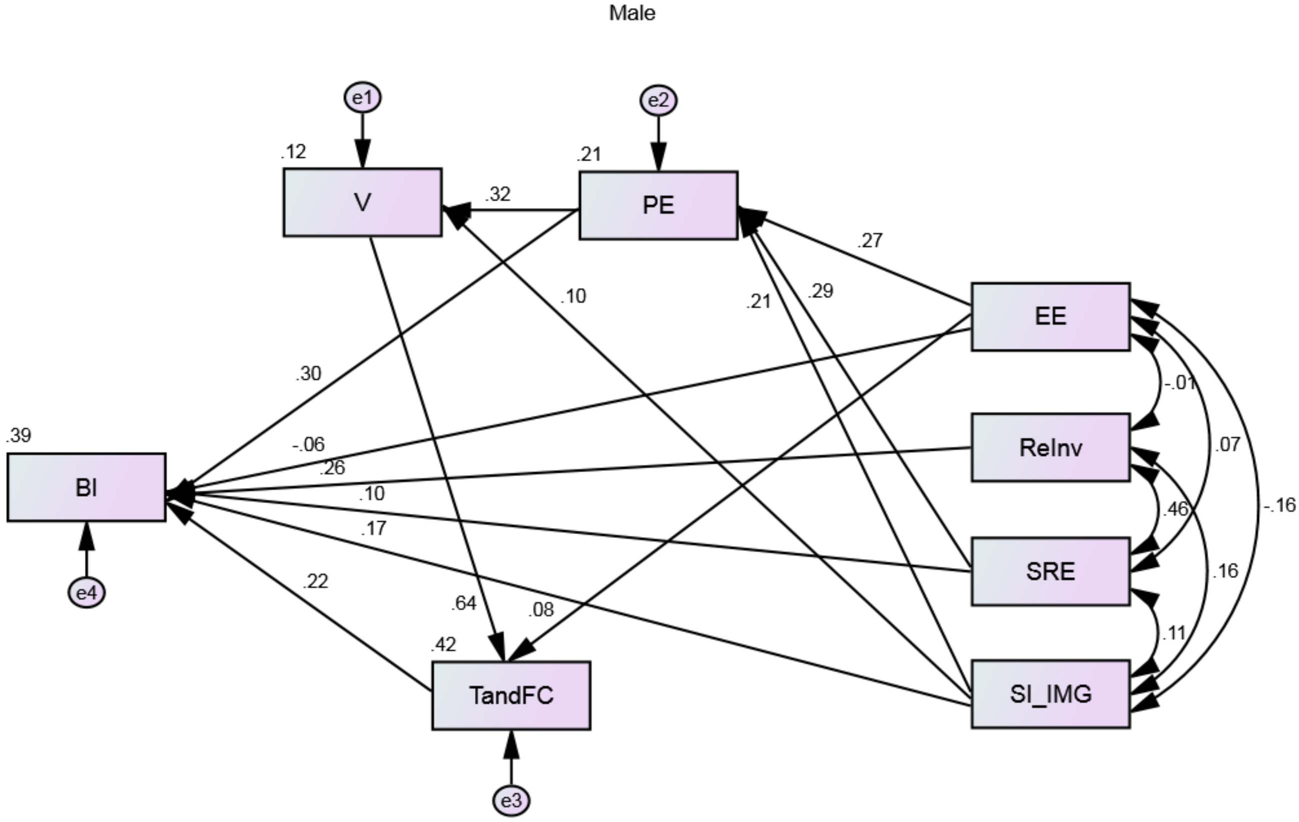
SRE_2	.000	.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.000	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.000	.000	.000	.000	.000
EE_5	.000	.000	.000	.000	.000	.000	.000	.000
V_3	.179	.100	.000	.048	.226	.000	.000	.000
V_4	.164	.092	.000	.044	.207	.000	.000	.000
T_2	.117	.066	.000	.031	.147	.654	.000	.000
T_1	.116	.065	.000	.031	.147	.650	.000	.000
PE_4	.175	.408	.000	.196	.000	.000	.000	.000
PE_2	.182	.423	.000	.203	.000	.000	.000	.000
PE_3	.191	.445	.000	.213	.000	.000	.000	.000
BI_3	.219	.314	.259	.005	.262	.111	.171	.000
BI_2	.209	.299	.247	.005	.250	.106	.163	.000
BI_1	.217	.310	.256	.005	.259	.110	.169	.000

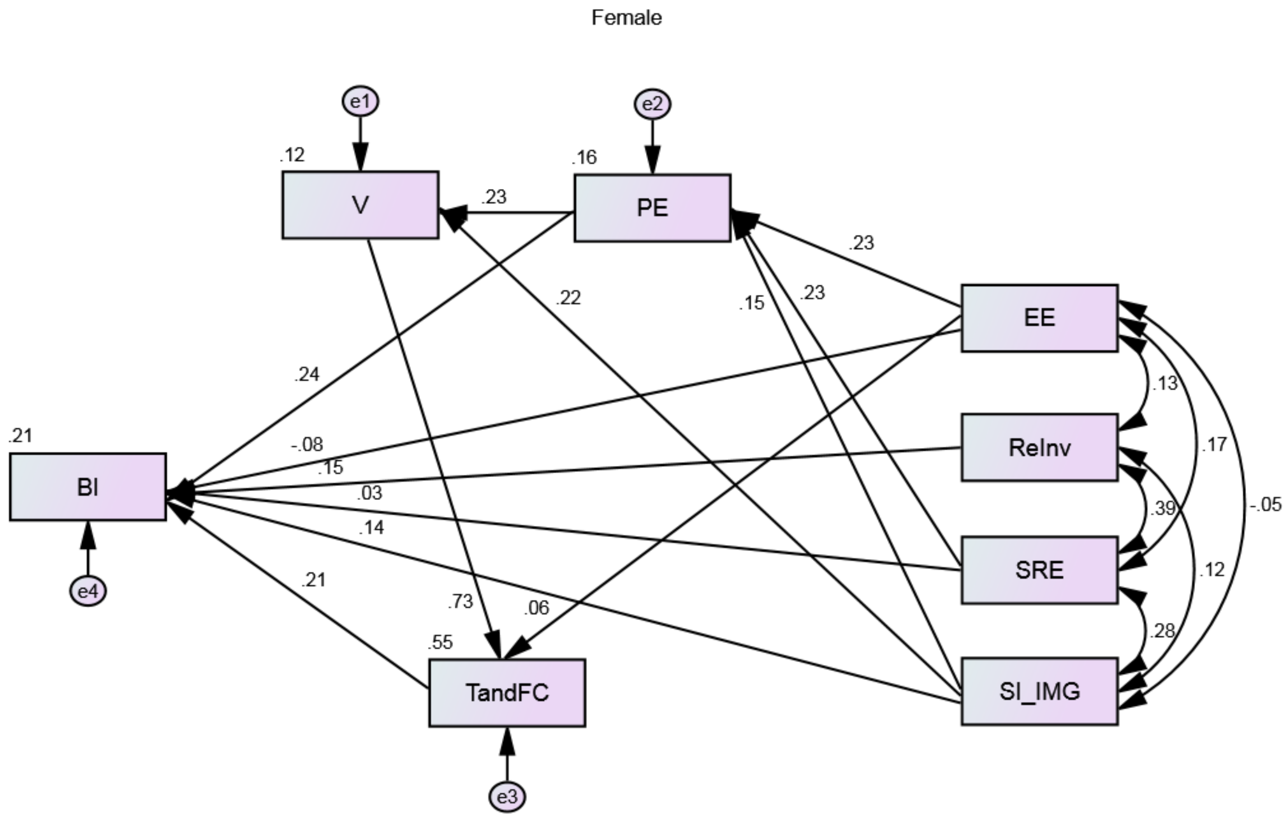
Standardised Indirect Effects (Post-Hoc model)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
PE	.000	.000	.000	.000	.000	.000	.000	.000
V	.045	.065	.000	.062	.000	.000	.000	.000
TandFC	.112	.039	.000	.037	.151	.000	.000	.000
BI	.070	.077	.000	.073	.029	.114	.000	.000
FC_2	.059	.020	.000	.019	.080	.314	.000	.000
V_1	.132	.046	.000	.043	.178	.000	.000	.000

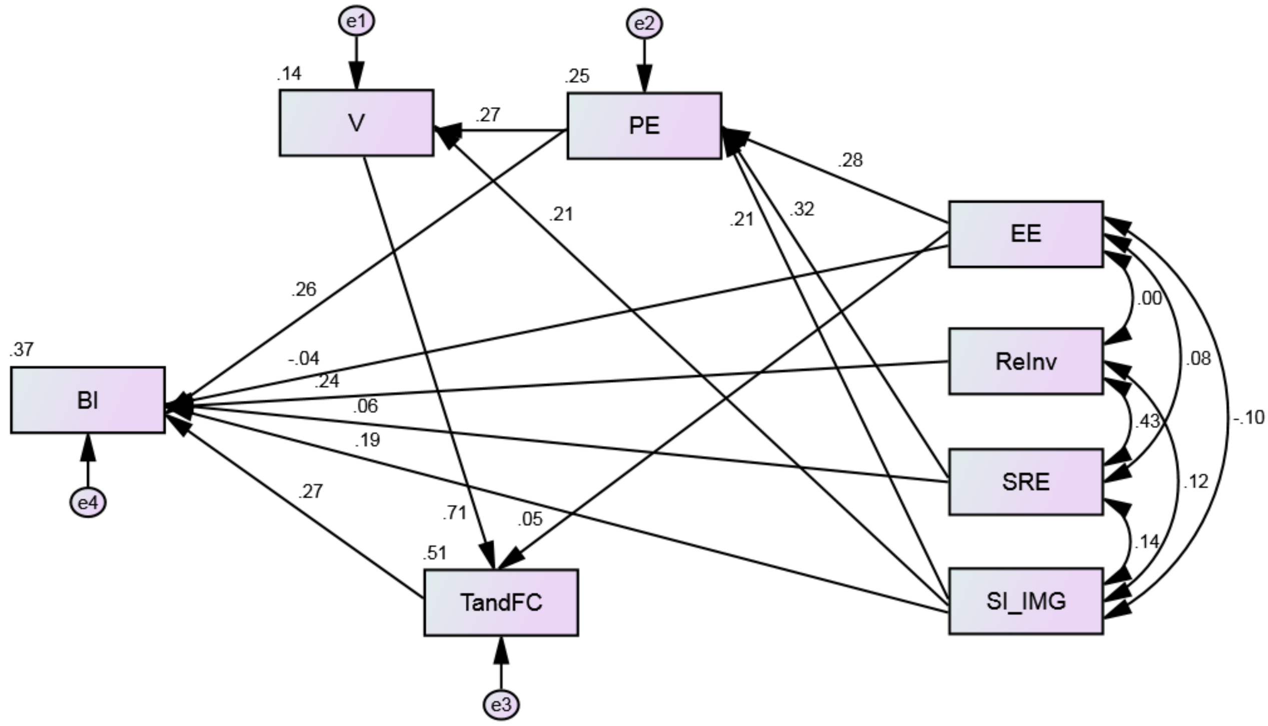
SI_7	.000	.000	.000	.000	.000	.000	.000	.000
SI_6	.000	.000	.000	.000	.000	.000	.000	.000
SRE_1	.000	.000	.000	.000	.000	.000	.000	.000
SRE_2	.000	.000	.000	.000	.000	.000	.000	.000
ReInv_3	.000	.000	.000	.000	.000	.000	.000	.000
ReInv_2	.000	.000	.000	.000	.000	.000	.000	.000
EE_6	.000	.000	.000	.000	.000	.000	.000	.000
EE_5	.000	.000	.000	.000	.000	.000	.000	.000
V_3	.160	.055	.000	.053	.217	.000	.000	.000
V_4	.144	.050	.000	.047	.195	.000	.000	.000
T_2	.099	.034	.000	.033	.134	.529	.000	.000
T_1	.097	.033	.000	.032	.131	.518	.000	.000
PE_4	.153	.219	.000	.208	.000	.000	.000	.000
PE_2	.158	.226	.000	.216	.000	.000	.000	.000
PE_3	.168	.240	.000	.229	.000	.000	.000	.000
BI_3	.225	.198	.174	.007	.288	.109	.182	.000
BI_2	.223	.197	.173	.007	.286	.108	.181	.000
BI_1	.227	.200	.175	.007	.291	.110	.184	.000

Appendix 17: Post-Hoc Moderated Models

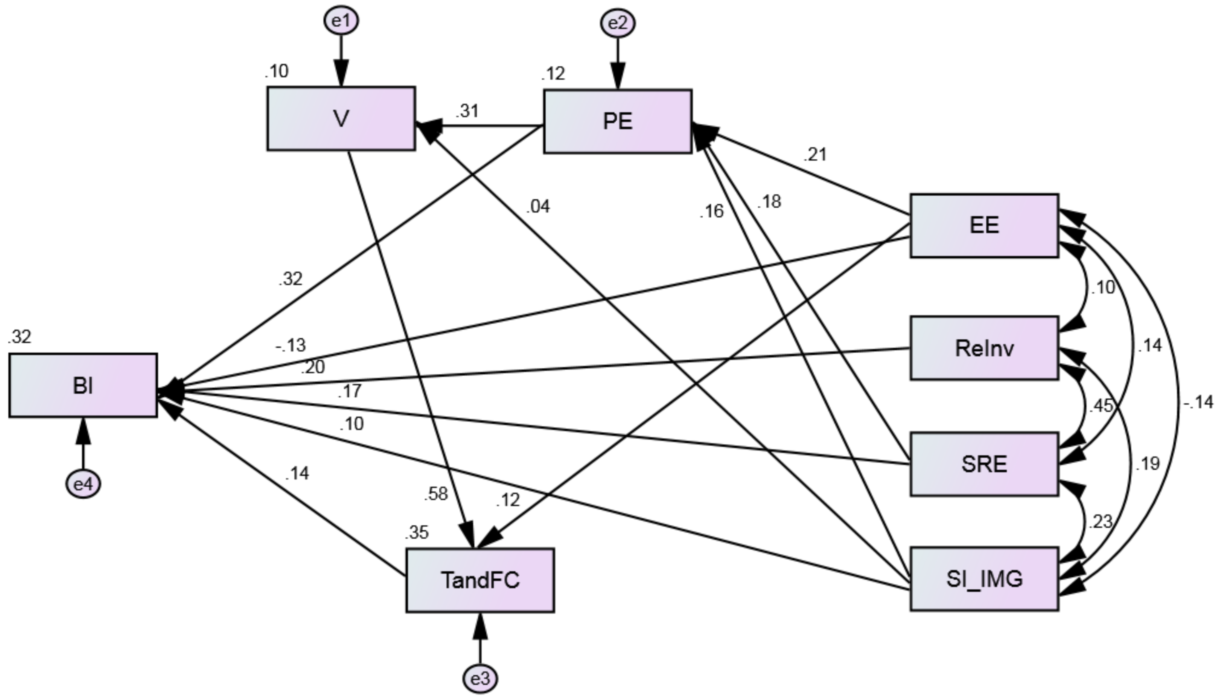




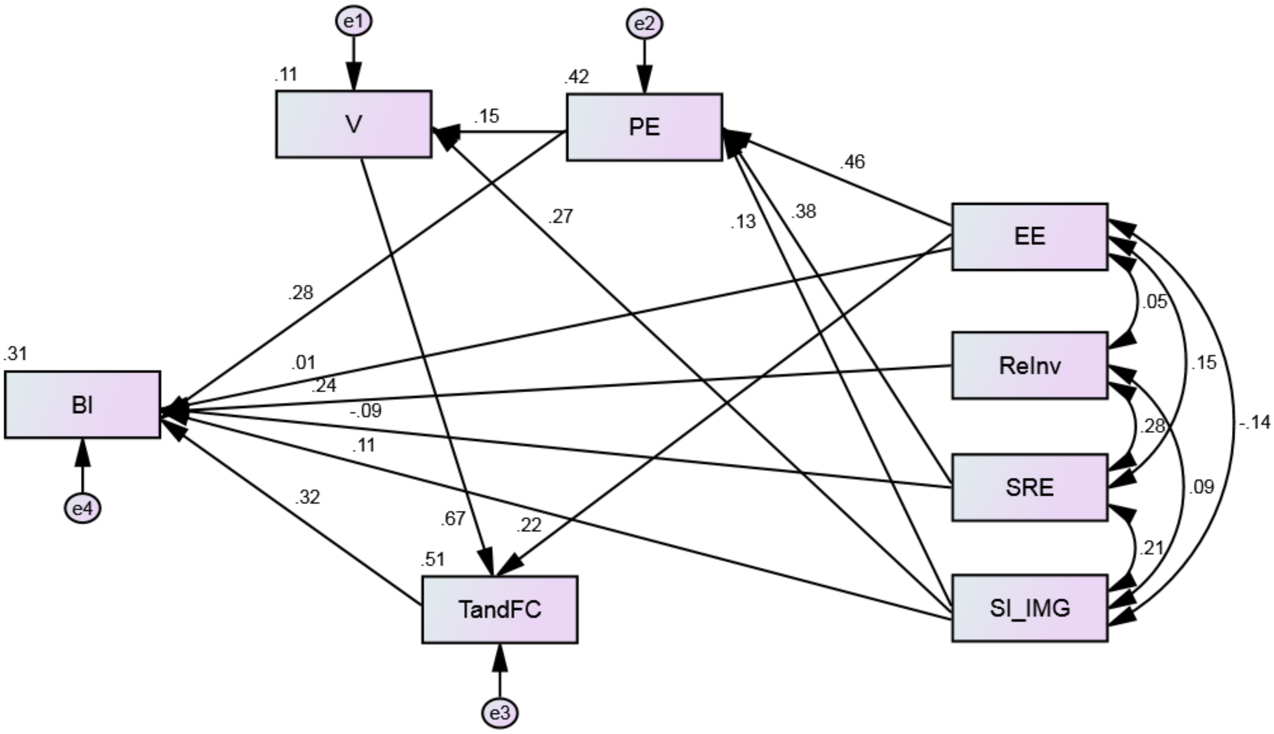
30-50 Years



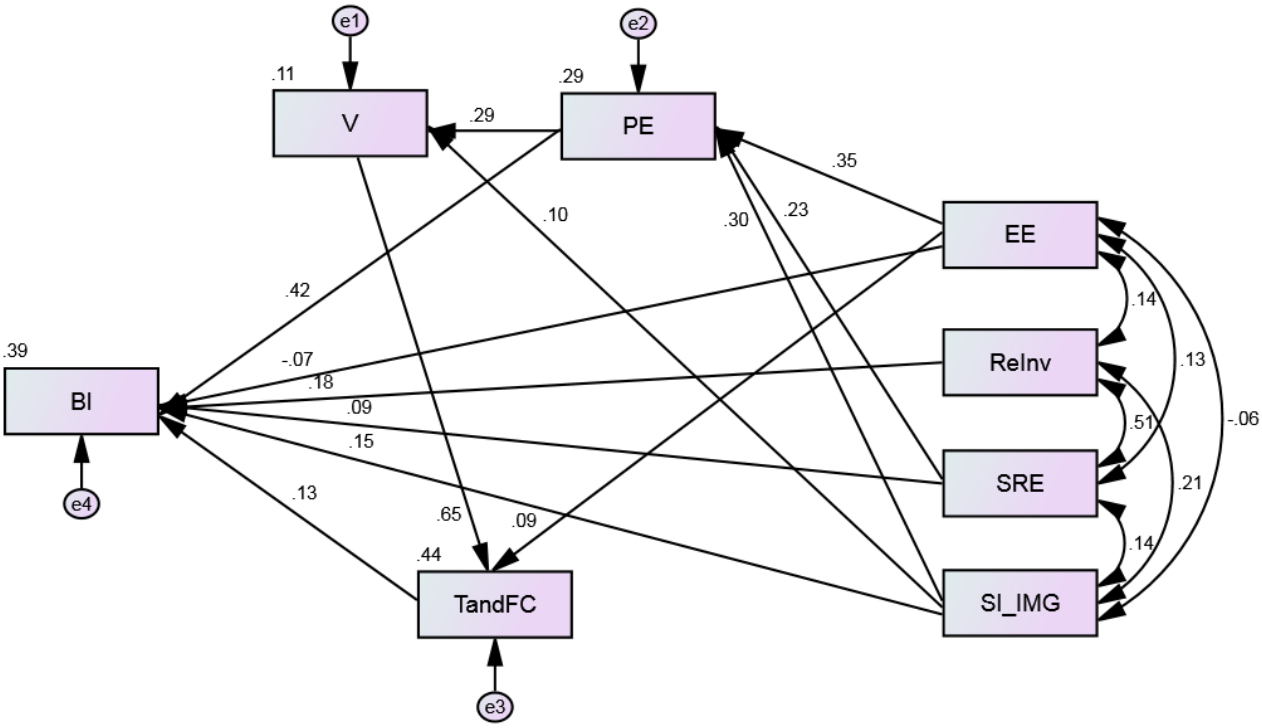
Over 50 Years



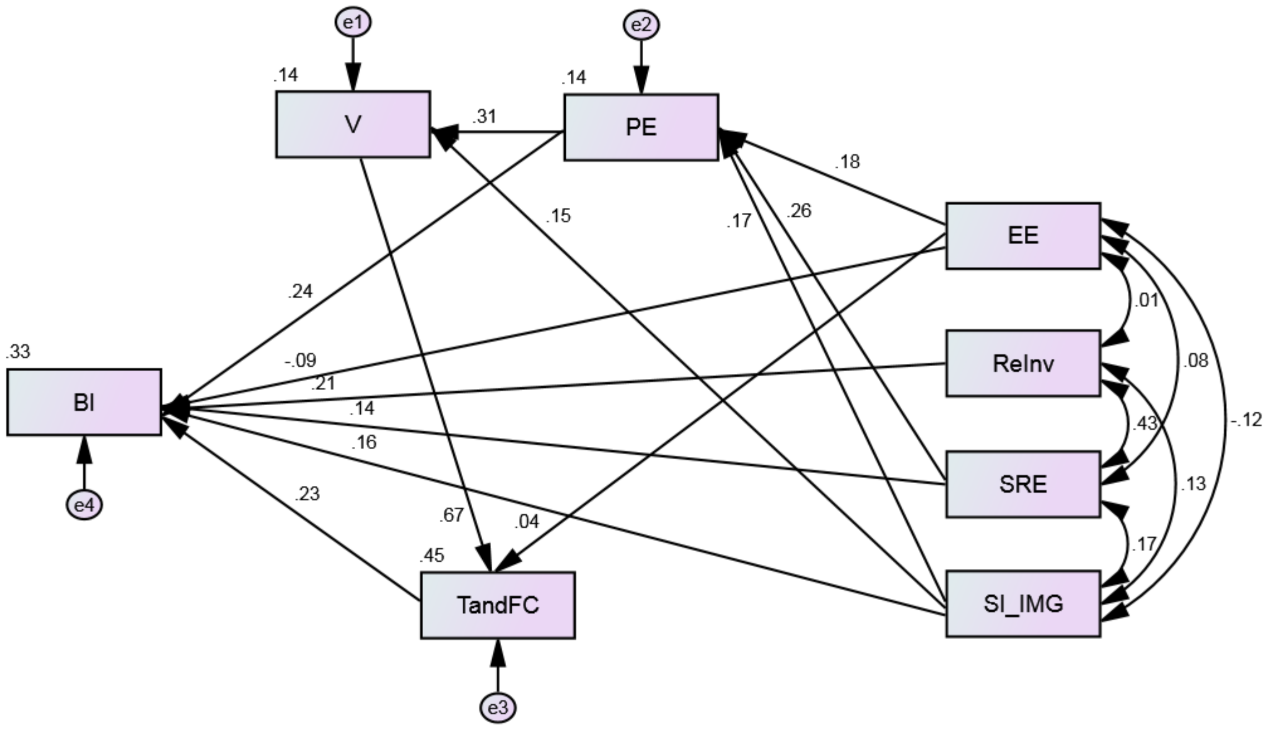
Less than 5 Years



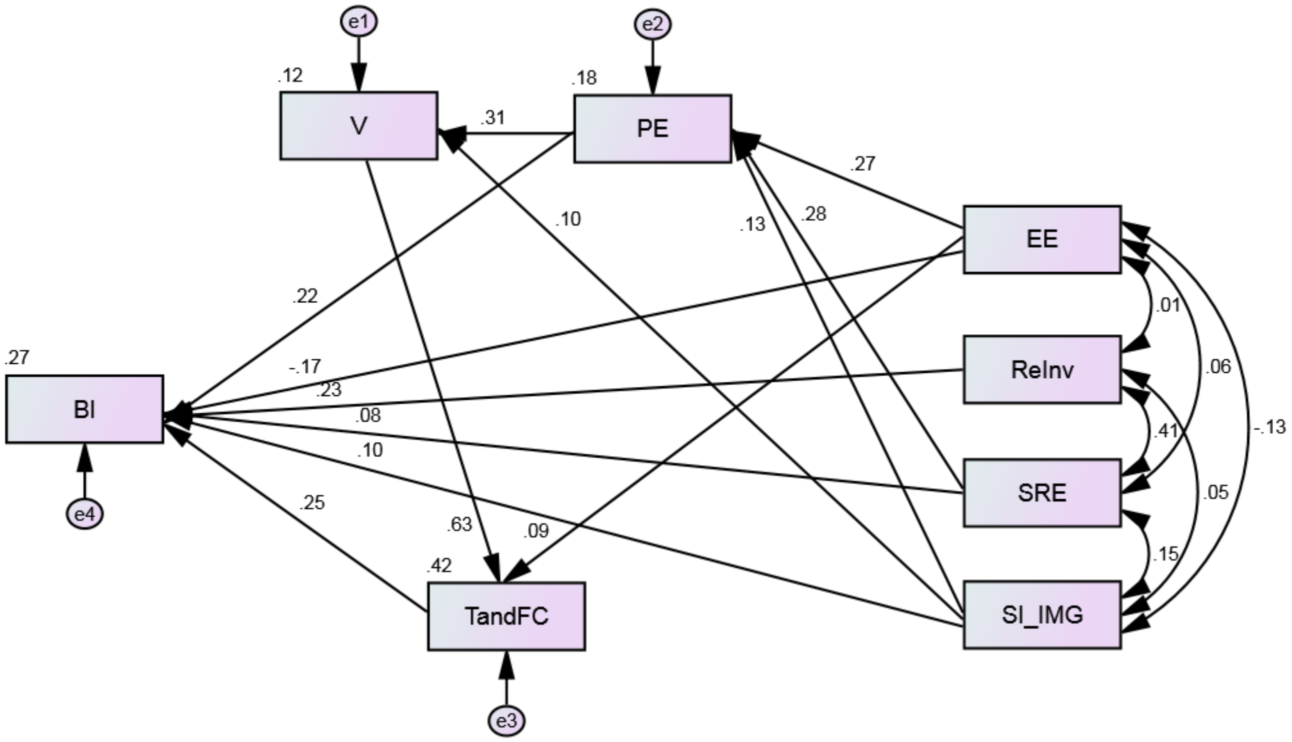
5-9 Years



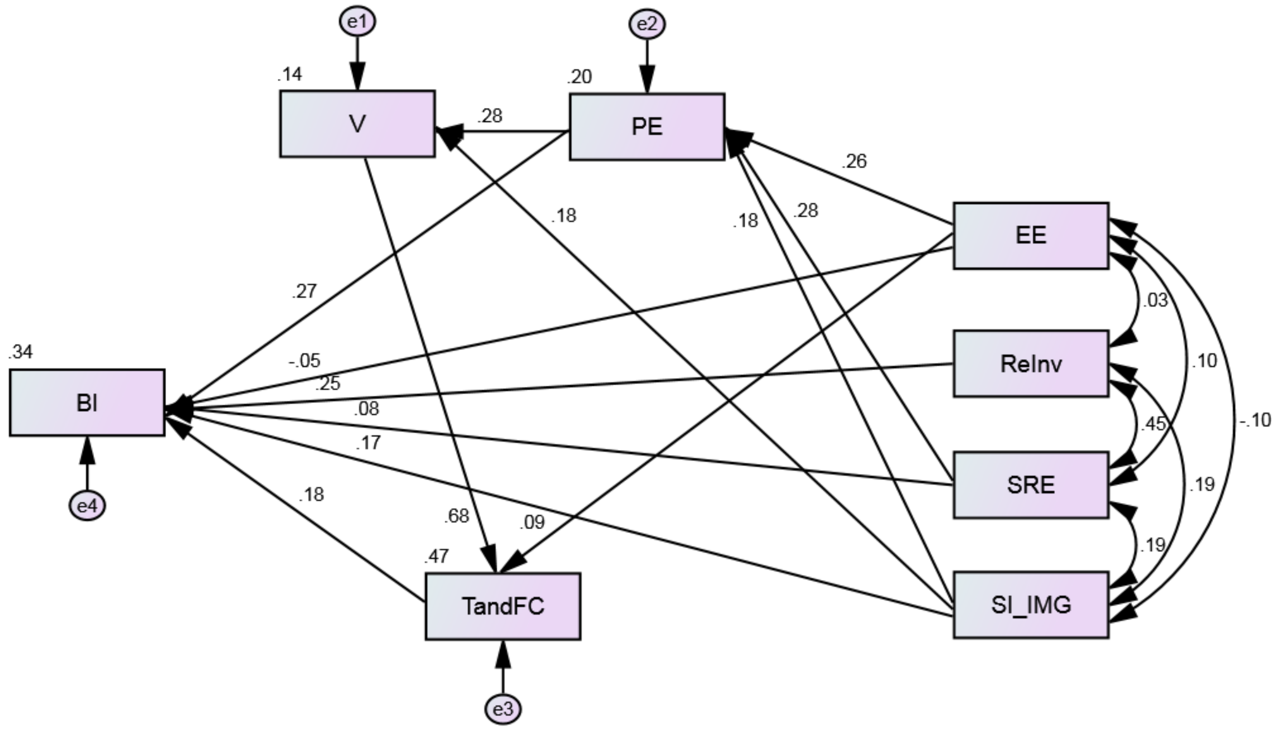
More than 9 Years



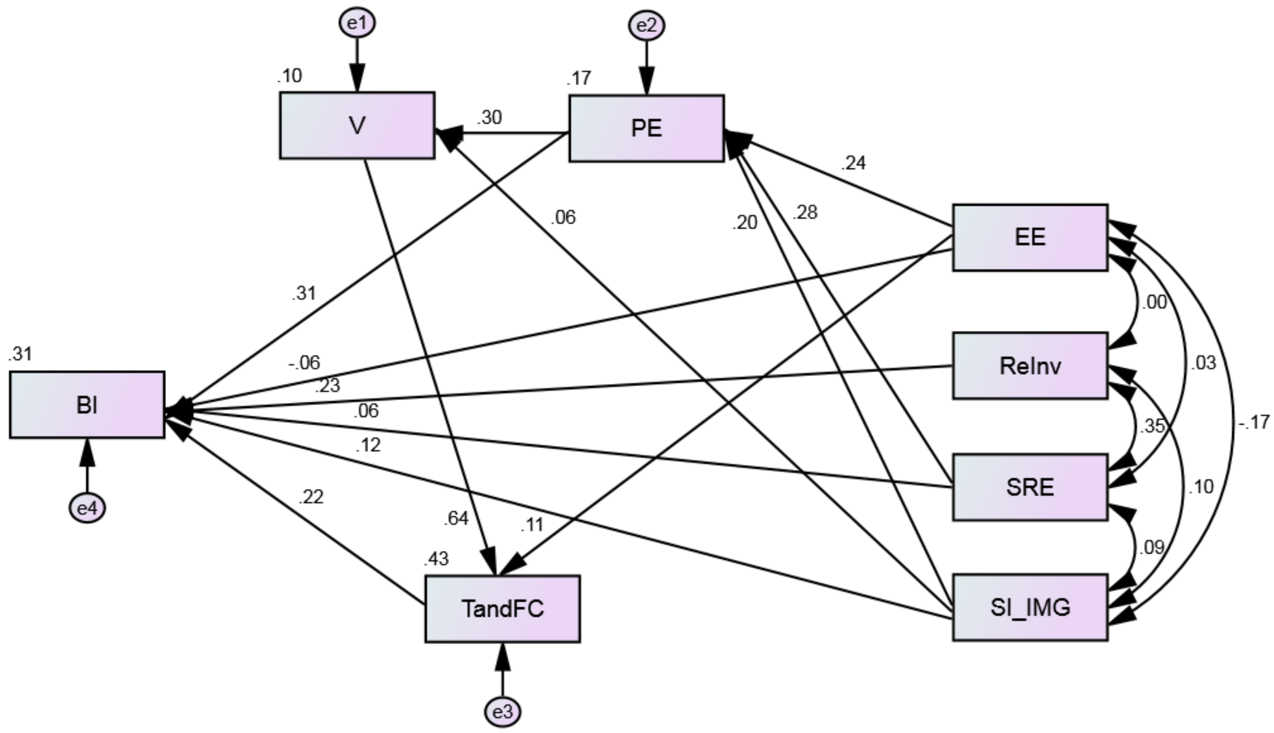
MSc



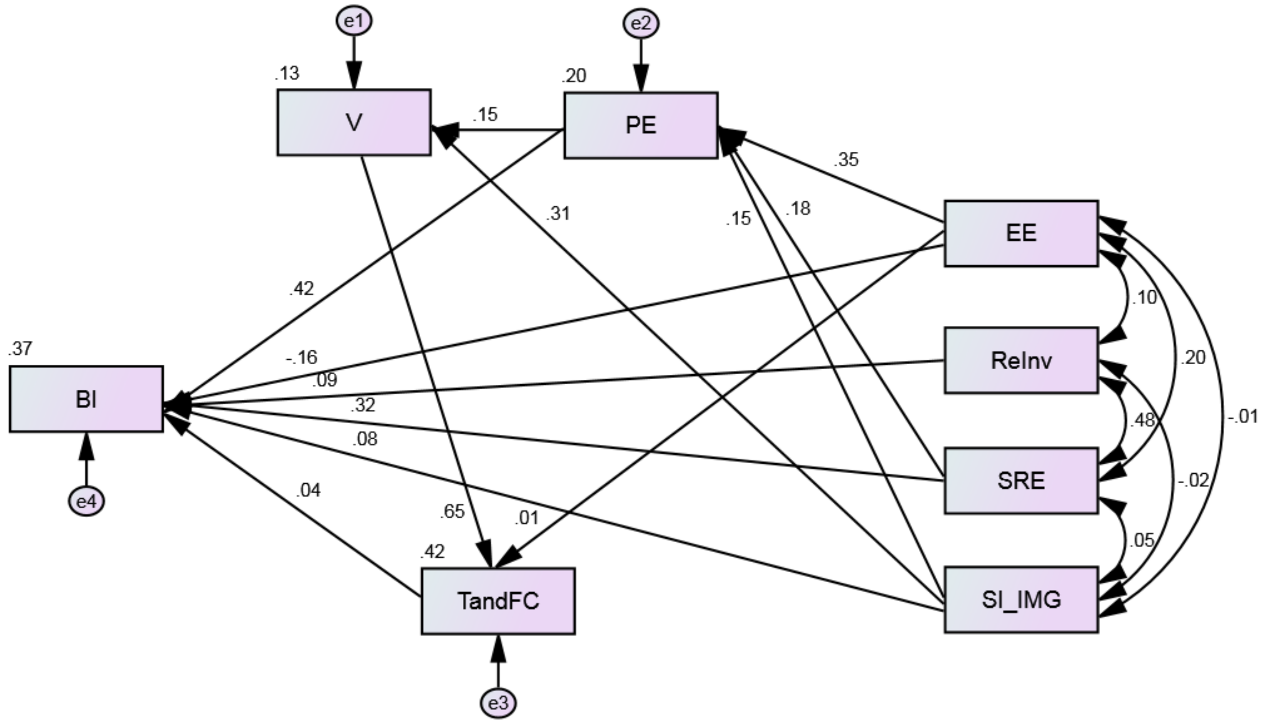
Doctorate



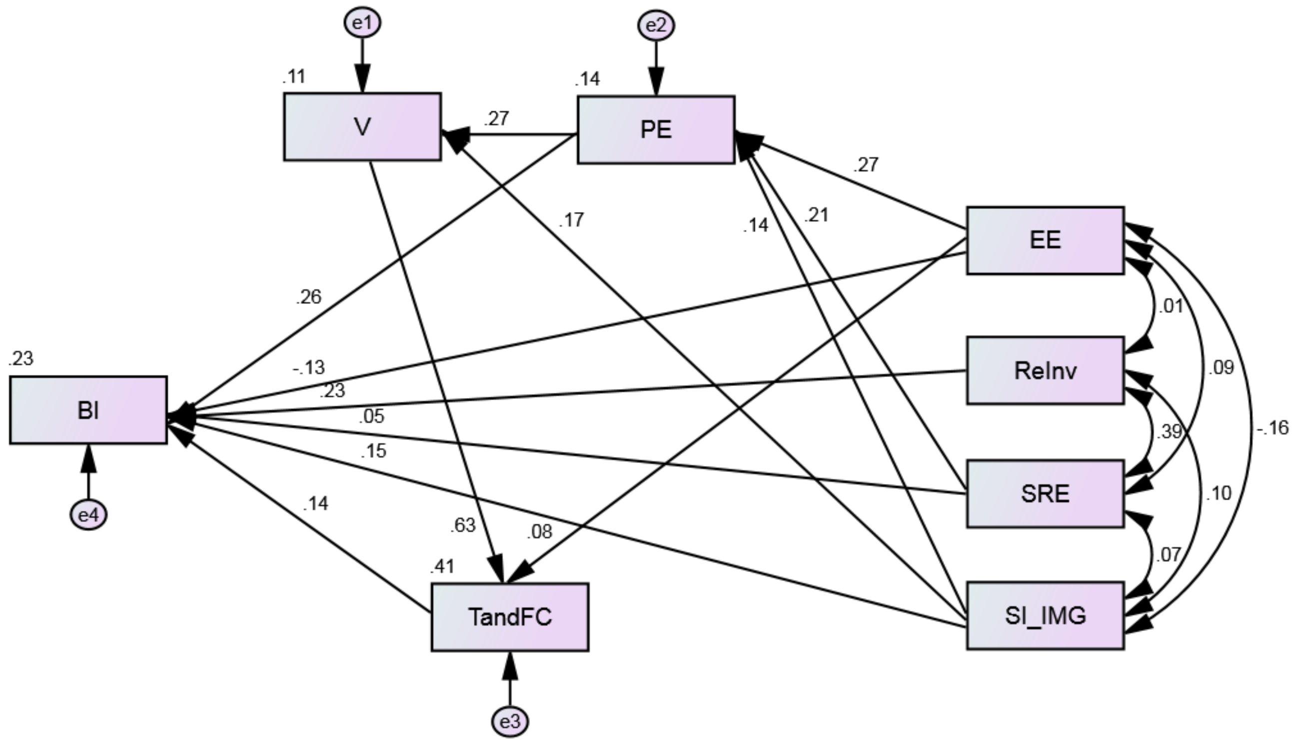
51-500 Hours/Year



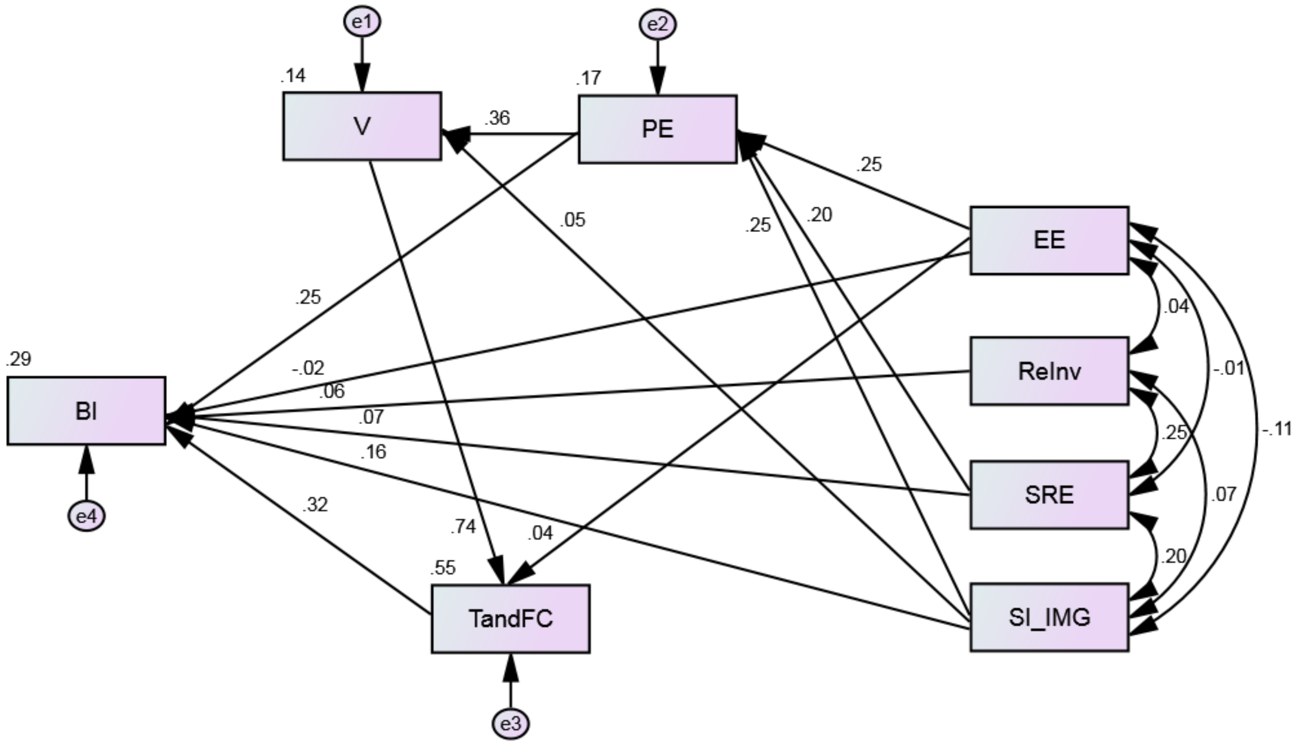
501-1000 Hours/Year



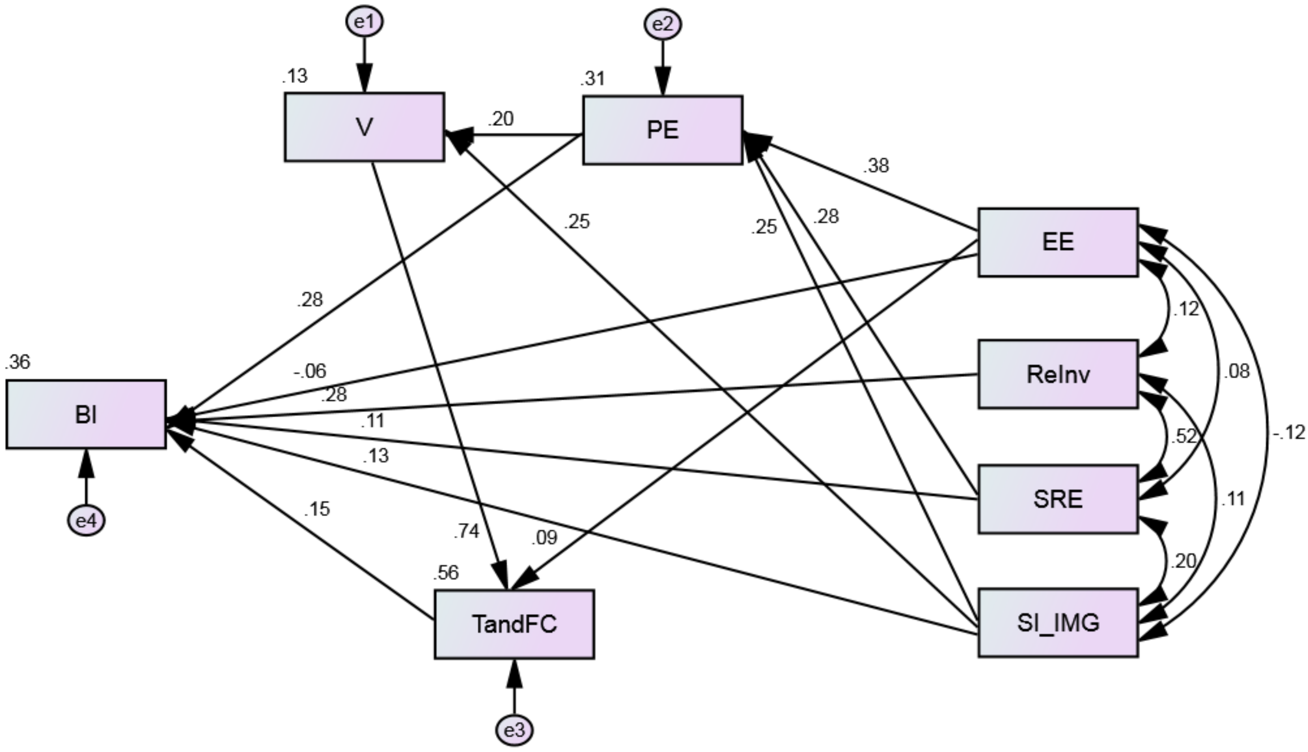
Voluntary



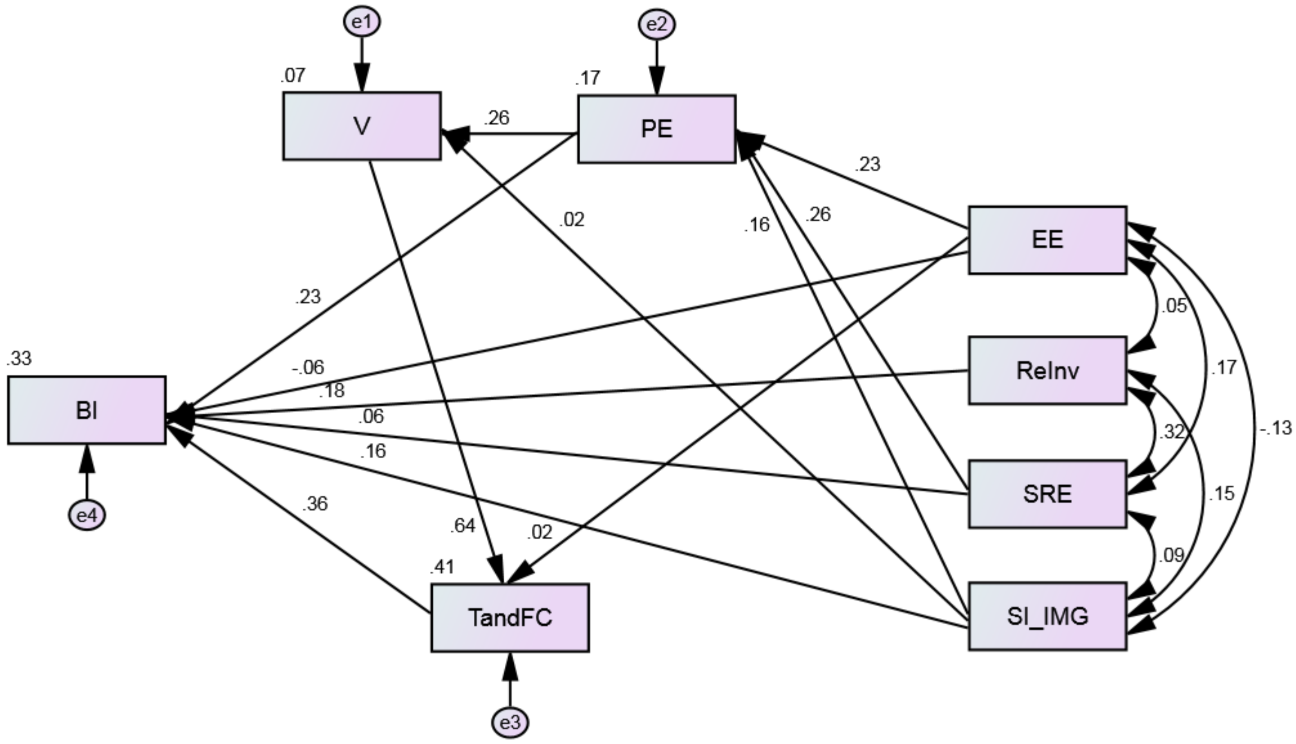
Mandatory



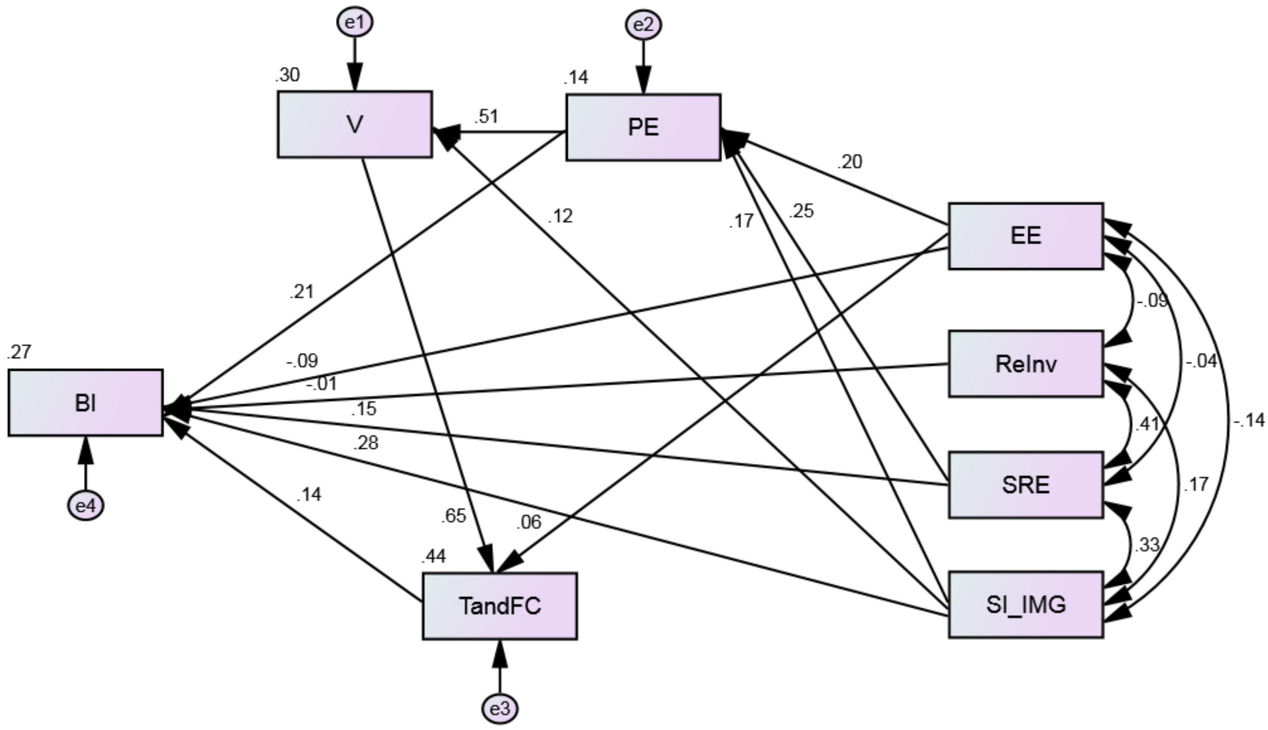
England



Scotland



Wales



Appendix 18: Post-Hoc Model Moderated Groups Z-Scores for differences

Major differences in the tables are highlighted. Rows highlighted in light green indicate the differences (z-score) are significant while rows highlighted in light grey show values worth discussing due to noticeable differences in the p-value or the estimates (i.e. strength of the effect). In all highlighted cases, at least one group must have a significant p-vaule < 0.05.

Gender

The moderated model had a CMIN/DF=1.940, p-value=.010, GFI=.982, CFI=.978, and RMSEA=.035 indicating a good fit.

			Male		Female		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.237	0.000	0.204	0.000	-0.428
PE	<---	SRE	0.466	0.000	0.479	0.001	0.072
PE	<---	SI_IMG	0.218	0.000	0.158	0.042	-0.632
V	<---	PE	0.262	0.000	0.200	0.001	-0.791
V	<---	SI_IMG	0.087	0.073	0.213	0.002	1.508
TandFC	<---	V	0.706	0.000	0.792	0.000	1.157
TandFC	<---	EE	0.064	0.075	0.053	0.208	-0.200
BI	<---	EE	-0.051	0.204	-0.052	0.274	-0.014
BI	<---	ReInv	0.427	0.000	0.211	0.037	-1.609
BI	<---	SRE	0.150	0.073	0.048	0.690	-0.689
BI	<---	SI_IMG	0.165	0.000	0.115	0.052	-0.656
BI	<---	TandFC	0.224	0.000	0.168	0.003	-0.758
BI	<---	PE	0.282	0.000	0.189	0.000	-1.242

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Age

The moderated model had a CMIN/DF=1.977, p-value=.008, GFI=.981, CFI=.976, and RMSEA=.046 indicating a good fit.

			30-50 Years		Over 50 Years		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.243	0.000	0.189	0.003	-0.703
PE	<---	SRE	0.566	0.000	0.296	0.011	-1.795*
PE	<---	SI_IMG	0.217	0.000	0.167	0.028	-0.536
V	<---	PE	0.235	0.000	0.249	0.000	0.186
V	<---	SI_IMG	0.192	0.000	0.037	0.541	-1.943*
TandFC	<---	V	0.781	0.000	0.628	0.000	-1.916*
TandFC	<---	EE	0.040	0.257	0.093	0.044	0.910
BI	<---	EE	-0.029	0.431	-0.114	0.039	-1.279
BI	<---	RelInv	0.391	0.000	0.310	0.004	-0.587
BI	<---	SRE	0.084	0.314	0.267	0.016	1.317
BI	<---	SI_IMG	0.164	0.000	0.101	0.128	-0.802
BI	<---	TandFC	0.232	0.000	0.159	0.021	-0.891
BI	<---	PE	0.213	0.000	0.314	0.000	1.270

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Experience

The moderated model had a CMIN/DF=1.185, p-value=.232, GFI=.983, CFI=.993, and RMSEA=.020 indicating a good fit.

			Less than 5 Years		5-9 Years		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.360	0.000	0.363	0.000	0.023

PE	<---	SRE	0.604	0.000	0.408	0.009	-0.910
PE	<---	SI_IMG	0.117	0.173	0.381	0.000	1.877*
V	<---	PE	0.161	0.172	0.221	0.004	0.433
V	<---	SI_IMG	0.260	0.017	0.101	0.305	-1.086
TandFC	<---	V	0.751	0.000	0.693	0.000	-0.472
TandFC	<---	EE	0.207	0.007	0.071	0.270	-1.355
BI	<---	EE	0.009	0.903	-0.061	0.402	-0.678
BI	<---	ReInv	0.327	0.019	0.290	0.052	-0.179
BI	<---	SRE	-0.116	0.420	0.128	0.348	1.231
BI	<---	SI_IMG	0.078	0.302	0.149	0.094	0.612
BI	<---	TandFC	0.211	0.002	0.133	0.102	-0.737
BI	<---	PE	0.219	0.029	0.334	0.000	0.905

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			5-9 Years		More than 9 Years		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.363	0.000	0.156	0.000	-2.058**
PE	<---	SRE	0.408	0.009	0.433	0.000	0.137
PE	<---	SI_IMG	0.381	0.000	0.170	0.003	-1.696*
V	<---	PE	0.221	0.004	0.262	0.000	0.446
V	<---	SI_IMG	0.101	0.305	0.125	0.008	0.223
TandFC	<---	V	0.693	0.000	0.731	0.000	0.401
TandFC	<---	EE	0.071	0.270	0.029	0.390	-0.580
BI	<---	EE	-0.061	0.402	-0.067	0.081	-0.081
BI	<---	ReInv	0.290	0.052	0.341	0.000	0.294
BI	<---	SRE	0.128	0.348	0.214	0.014	0.529

BI	<---	SI_IMG	0.149	0.094	0.151	0.001	0.016
BI	<---	TandFC	0.133	0.102	0.230	0.000	1.026
BI	<---	PE	0.334	0.000	0.227	0.000	-1.167

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			Less than 5 Years		More than 9 Years		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.360	0.000	0.156	0.000	-2.374**
PE	<---	SRE	0.604	0.000	0.433	0.000	-0.974
PE	<---	SI_IMG	0.117	0.173	0.170	0.003	0.510
V	<---	PE	0.161	0.172	0.262	0.000	0.800
V	<---	SI_IMG	0.260	0.017	0.125	0.008	-1.138
TandFC	<---	V	0.751	0.000	0.731	0.000	-0.195
TandFC	<---	EE	0.207	0.007	0.029	0.390	-2.131**
BI	<---	EE	0.009	0.903	-0.067	0.081	-0.927
BI	<---	ReInv	0.327	0.019	0.341	0.000	0.086
BI	<---	SRE	-0.116	0.420	0.214	0.014	1.962**
BI	<---	SI_IMG	0.078	0.302	0.151	0.001	0.822
BI	<---	TandFC	0.211	0.002	0.230	0.000	0.228
BI	<---	PE	0.219	0.029	0.227	0.000	0.072

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Education

The moderated model had a CMIN/DF=.898, p-value=.581, GFI=.991, CFI=1.000, and RMSEA=.000 indicating a good fit.

			MSc		Doctorate		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.215	0.005	0.232	0.000	0.191
PE	<---	SRE	0.456	0.004	0.481	0.000	0.137
PE	<---	SI_IMG	0.114	0.196	0.195	0.000	0.778
V	<---	PE	0.301	0.002	0.232	0.000	-0.648
V	<---	SI_IMG	0.087	0.315	0.165	0.000	0.784
TandFC	<---	V	0.667	0.000	0.735	0.000	0.698
TandFC	<---	EE	0.073	0.261	0.074	0.020	0.011
BI	<---	EE	-0.114	0.080	-0.037	0.333	1.026
BI	<---	RelInv	0.316	0.025	0.414	0.000	0.599
BI	<---	SRE	0.114	0.434	0.130	0.106	0.101
BI	<---	SI_IMG	0.073	0.314	0.167	0.000	1.101
BI	<---	TandFC	0.214	0.007	0.182	0.000	-0.348
BI	<---	PE	0.189	0.032	0.245	0.000	0.559

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Teaching Hours

The resulting moderated model had a CMIN/DF=1.236, p-value=.221, GFI=.986, CFI=.992, and RMSEA=.025 indicating a good fit.

			51-500 Hours/Year		501-1000 Hours/Year		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.211	0.000	0.273	0.000	0.663
PE	<---	SRE	0.494	0.000	0.317	0.081	-0.876
PE	<---	SI_IMG	0.221	0.000	0.150	0.149	-0.595
V	<---	PE	0.255	0.000	0.130	0.149	-1.233
V	<---	SI_IMG	0.059	0.239	0.267	0.004	1.975**
TandFC	<---	V	0.719	0.000	0.661	0.000	-0.575
TandFC	<---	EE	0.089	0.013	0.010	0.865	-1.144

BI	<---	EE	-0.044	0.240	-0.100	0.114	-0.771
BI	<---	RelInv	0.347	0.000	0.120	0.367	-1.479
BI	<---	SRE	0.088	0.253	0.459	0.003	2.178**
BI	<---	SI_IMG	0.115	0.011	0.063	0.422	-0.566
BI	<---	TandFC	0.201	0.000	0.034	0.695	-1.697*
BI	<---	PE	0.262	0.000	0.342	0.000	0.845

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Voluntary/Mandatory Adoption

The moderated model had a CMIN/DF=1.001, p-value=.454, GFI=.990, CFI=1.000, and RMSEA=.002 indicating a good fit.

			Voluntary		Mandatory		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.220	0.000	0.228	0.004	0.088
PE	<---	SRE	0.373	0.000	0.354	0.026	-0.098
PE	<---	SI_IMG	0.149	0.007	0.253	0.005	0.989
V	<---	PE	0.235	0.000	0.311	0.000	0.831
V	<---	SI_IMG	0.153	0.002	0.042	0.593	-1.197
TandFC	<---	V	0.665	0.000	0.801	0.000	1.639
TandFC	<---	EE	0.058	0.077	0.031	0.561	-0.422
BI	<---	EE	-0.087	0.011	-0.014	0.820	1.021
BI	<---	RelInv	0.329	0.000	0.086	0.489	-1.668*
BI	<---	SRE	0.064	0.414	0.112	0.383	0.321
BI	<---	SI_IMG	0.125	0.003	0.133	0.062	0.088
BI	<---	TandFC	0.117	0.009	0.280	0.000	1.89*
BI	<---	PE	0.206	0.000	0.206	0.006	0.000

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Country

The moderated model had a CMIN/DF=1.633, p-value=.0, GFI=.841, CFI=.934, and RMSEA=.038 indicating a good fit.

			England		Scotland		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.349	0.000	0.186	0.002	-1.897*
PE	<---	SRE	0.471	0.000	0.418	0.000	-0.324
PE	<---	SI_IMG	0.281	0.000	0.162	0.031	-1.122
V	<---	PE	0.167	0.009	0.243	0.001	0.772
V	<---	SI_IMG	0.234	0.000	0.023	0.756	-2.061**
TandFC	<---	V	0.773	0.000	0.715	0.000	-0.646
TandFC	<---	EE	0.077	0.067	0.016	0.759	-0.905
BI	<---	EE	-0.055	0.363	-0.041	0.434	0.180
BI	<---	ReInv	0.471	0.000	0.273	0.012	-1.214
BI	<---	SRE	0.167	0.163	0.083	0.444	-0.517
BI	<---	SI_IMG	0.141	0.048	0.149	0.018	0.085
BI	<---	TandFC	0.163	0.018	0.314	0.000	1.661*
BI	<---	PE	0.265	0.000	0.215	0.002	-0.513

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			Scotland		Wales		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.186	0.002	0.176	0.032	-0.100
PE	<---	SRE	0.418	0.000	0.444	0.013	0.123
PE	<---	SI_IMG	0.162	0.031	0.167	0.097	0.038
V	<---	PE	0.243	0.001	0.387	0.000	1.440
V	<---	SI_IMG	0.023	0.756	0.095	0.154	0.725

TandFC	<---	V	0.715	0.000	0.783	0.000	0.589
TandFC	<---	EE	0.016	0.759	0.045	0.457	0.359
BI	<---	EE	-0.041	0.434	-0.066	0.306	-0.306
BI	<---	RelInv	0.273	0.012	-0.019	0.895	-1.620
BI	<---	SRE	0.083	0.444	0.218	0.149	0.725
BI	<---	SI_IMG	0.149	0.018	0.229	0.003	0.797
BI	<---	TandFC	0.314	0.000	0.128	0.128	-1.806*
BI	<---	PE	0.215	0.002	0.171	0.036	-0.411

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

			England		Wales		
			Estimate	P	Estimate	P	z-score
PE	<---	EE	0.349	0.000	0.176	0.032	-1.703*
PE	<---	SRE	0.471	0.000	0.444	0.013	-0.127
PE	<---	SI_IMG	0.281	0.000	0.167	0.097	-0.909
V	<---	PE	0.167	0.009	0.387	0.000	2.39**
V	<---	SI_IMG	0.234	0.000	0.095	0.154	-1.426
TandFC	<---	V	0.773	0.000	0.783	0.000	0.097
TandFC	<---	EE	0.077	0.067	0.045	0.457	-0.440
BI	<---	EE	-0.055	0.363	-0.066	0.306	-0.125
BI	<---	RelInv	0.471	0.000	-0.019	0.895	-2.599***
BI	<---	SRE	0.167	0.163	0.218	0.149	0.266
BI	<---	SI_IMG	0.141	0.048	0.229	0.003	0.835
BI	<---	TandFC	0.163	0.018	0.128	0.128	-0.319
BI	<---	PE	0.265	0.000	0.171	0.036	-0.872

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

Appendix 19: Establishing Mediation effects in Post-Hoc Model

The following table establishes the relationships between IVs and the DV (BI) without any mediator present:

Standardised Regression Weights: (No Mediators)

DV		IV	Estimate	P
BI	<---	EE	0.025	0.551
BI	<---	ReInv	0.205	***
BI	<---	SRE	0.211	***
BI	<---	SI_IMG	0.233	***

As can be seen, all paths are significant, except for EE —> BI.

Additionally, the researcher looked at establishing the significance of IVs to DV (TandFC) for the potential mediation of V for both PE and SI_IMG. The following table shows that the path from PE —> TandFC is significant while the other path is not.

Standardised Regression Weights:

(IVs to TandFC)

DV		IV	Estimate	P
TandFC	<---	PE	0.035	0.329
TandFC	<---	SI_IMG	-0.021	0.55

Similarly, the researcher looked at establishing the significance of IVs to DV (V) for the potential mediation of PE for EE and SI_IMG. The following table shows that both paths are significant without the mediator.

Standardised Regression Weights:

(IVs to V)

	Estimate	P
V <--- SI_IMG	0.223	***
V <--- EE	0.125	0.006

Next, we establish the relationship between the IVs and the mediators (PE, TandFC, V) by running the model with the mediators and capturing estimates:

Standardised Regression Weights:

(IVs to TandFC)

DV		IV	Estimate	P
TandFC	<---	EE	0.139	0.002
TandFC	<---	SI_IMG	0.108	0.019
TandFC	<---	SRE	0.137	0.003

Standardised Regression Weights:

(IVs to PE)

DV		IV	Estimate	P
PE	<---	EE	0.258	***
PE	<---	SI_IMG	0.186	***
PE	<---	SRE	0.265	***

Standardised Regression Weights:

(IVs to V)

DV		IV	Estimate	P
V	<---	PE	0.281	***
V	<---	SI_IMG	0.151	***

The above tables established that all paths from IVs to the mediators are significant.

Finally, we investigate the paths between the mediators to the dependent variables and compare that to all the paths without the moderators:

Standardised Regression Weights: (No Mediators)					Standardised Regression Weights: (All Mediators & Direct Paths)				
DV		IV	Estimate	P	DV		IV	Estimate	P
BI	<---	EE	0.025	0.551	BI	<---	EE	-0.077	0.058
BI	<---	ReInv	0.205	***	BI	<---	ReInv	0.215	***
BI	<---	SRE	0.211	***	BI	<---	SRE	0.104	0.018
BI	<---	SI_IMG	0.233	***	BI	<---	SI_IMG	0.158	***
					BI	<---	TandFC	0.205	***
					BI	<---	PE	0.283	***
					PE	<---	EE	0.258	***
					PE	<---	SRE	0.265	***
					PE	<---	SI_IMG	0.186	***
					TandFC	<---	V	0.659	***
					TandFC	<---	EE	0.063	0.08
					TandFC	<---	PE	0.035	0.355
					TandFC	<---	SI_IMG	-0.021	0.562
					V	<---	PE	0.267	***
					V	<---	SI_IMG	0.16	***
					V	<---	EE	0.047	0.301

Table 9.1 Comparison between paths with and without mediators

Appendix 20: Predicting Use

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	497	100.0
	Missing Cases	0	.0
	Total	497	100.0
Unselected Cases		0	.0
Total		497	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Block 0: Beginning Block

Iteration History[a,b,c]

Iteration		-2 Log likelihood	Coefficients
			Constant
Step 0	1	320.119	1.646
	2	298.224	2.186
	3	297.334	2.323
	4	297.332	2.332
	5	297.332	2.332

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 297.332

c. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a,b]

	Observed		Predicted		
			IsAdopter		Percentage Correct
			No	Yes	
Step 0	IsAdopter	No	0	44	.0
		Yes	0	453	100.0
	Overall Percentage				91.1

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	2.332	.158	218.042	1	.000	10.295

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	SRE	27.329	1	.000
		TandFC	23.667	1	.000

		BI	58.856	1	.000
		Exp	6.780	1	.009
		THrsYear	17.496	1	.000
	Overall Statistics		88.373	5	.000

Block 1: Method = Enter

Iteration History[a,b,c,d]

Iteration		-2 Log likelihood	Coefficients					
			Constant	SRE	TandFC	BI	Exp	THrsYear
Step 1	1	279.578	-2.166	.177	.086	.260	.222	.187
	2	225.940	-5.490	.366	.207	.485	.486	.443
	3	213.239	-8.253	.529	.322	.626	.712	.693
	4	211.823	-9.518	.610	.378	.682	.814	.815
	5	211.796	-9.721	.624	.388	.690	.831	.834
	6	211.796	-9.725	.624	.388	.690	.831	.834
	7	211.796	-9.725	.624	.388	.690	.831	.834

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 297.332

d. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	85.535	5	.000
	Block	85.535	5	.000
	Model	85.535	5	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	211.796[a]	.158	.351

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	5.703	8	.680

Contingency Table for Hosmer and Lemeshow Test

		IsAdopter = No		IsAdopter = Yes		Total
		Observed	Expected	Observed	Expected	
Step 1	1	23	22.428	27	27.572	50
	2	6	8.507	44	41.493	50
	3	6	4.956	44	45.044	50
	4	2	2.930	48	47.070	50
	5	2	1.894	48	48.106	50
	6	3	1.319	47	48.681	50
	7	1	.877	49	49.123	50
	8	0	.595	50	49.405	50
	9	1	.345	49	49.655	50
	10	0	.149	47	46.851	47

Classification Table[a]

	Observed		Predicted		
			IsAdopter		Percentage Correct
			No	Yes	
Step1	IsAdopter	No	11	33	25.0
		Yes	4	449	99.1
	Overall Percentage				92.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	SRE	.624	.224	7.762	1	.005	**1.867**	1.203	2.897
	TandFC	.388	.153	6.435	1	.011	**1.474**	1.092	1.989
	BI	.690	.146	22.199	1	.000	**1.994**	1.496	2.657
	Exp	.831	.233	12.711	1	.000	**2.296**	1.454	3.626
	THrsYear	.834	.326	6.539	1	.011	**2.303**	1.215	4.366
	Constant	-9.725	1.689	33.152	1	.000	.000		

a. Variable(s) entered on step 1: SRE, TandFC, BI, Exp, THrsYear.

Appendix 21: Residuals of both models

Below are the standardised residuals covariances for both models. Residual covariances for the post-hoc model are presented before and after creating composites of the latent variables. An upper cut-off point of 2.85 standardised residual value is suggested (Byrne, 2010).

Standardised Residual Covariances (Model 1)

	FC_2	SL_1	SL_3	V_1	EE_4	SI_7	SI_6	SRE_1	SRE_2	ReInv_3	ReInv_2	SL_2	EE_6	EE_5	V_3	V_4	T_2	T_1	PE_4	PE_2	PE_3	BI_3	BI_2	BI_1
FC_2	.000																							
SL_1	-.399	.000																						
SL_3	-.215	-1.085	.000																					
V_1	-.550	-.386	1.057	.000																				
EE_4	1.587	3.035	3.311	3.842	.000																			
SI_7	-.956	-.596	1.209	.253	2.170	.000																		
SI_6	-1.091	-.619	1.598	.544	3.404	.001	.000																	
SRE_1	.234	1.040	.917	1.120	1.449	1.146	.479	.000																
SRE_2	1.155	-.773	3.138	.490	1.928	-.157	-.151	.000	.000															
ReInv_3	.036	.586	2.021	2.130	2.497	-.731	.443	-.624	.140	.000														
ReInv_2	-1.380	-.732	1.230	1.267	1.336	-1.634	-.402	-.265	.133	.000	.000													
SL_2	-.624	.675	-.189	-.562	3.350	-.911	-.395	-.494	-1.254	-.477	-1.051	.000												
EE_6	1.648	-.633	-.017	-.154	-.120	.180	.368	-.293	.005	-.450	-.782	.053	.000											
EE_5	1.085	-.742	.195	-.315	-.009	-.715	-.438	-.086	-.150	.057	.081	-.084	.011	.000										
V_3	-.624	-.365	.026	.177	3.563	.009	-.724	-.056	-.834	-.581	-.757	.032	.024	-.092	.000									
V_4	-.439	-.068	.948	-.347	3.246	1.236	.977	1.246	.620	-.271	.257	.162	-.298	-.596	-.003	.000								
T_2	.363	-.479	.766	-.115	3.896	-1.364	-1.092	-2.025	.379	.872	-.542	.351	.217	.681	-.435	-.370	.000							
T_1	-.169	-1.048	.467	.392	2.021	1.194	1.005	-1.291	.362	-.175	.197	.333	-1.303	-.835	.176	.686	-.021	.000						
PE_4	1.513	.044	.731	.311	3.543	1.139	.102	-.061	.533	1.605	-.387	-.251	.807	.542	-1.061	-.607	-.001	-.842	.000					
PE_2	.798	-.083	.806	.568	3.162	.834	-.281	-.751	-.324	.044	-1.461	-.216	1.433	.523	-.426	.556	-.162	-.319	-.064	.000				
PE_3	.964	-.411	1.015	.976	2.124	.925	.077	-.183	.136	.674	-.393	-.363	-.550	-1.019	-.322	.663	.396	-.130	-.014	.032	.000			
BI_3	.052	-1.582	2.656	2.606	3.878	-1.112	-.510	-.443	.276	-.132	-.584	-.532	.170	.064	-.861	.808	.842	.533	.764	-.370	.290	.000		
BI_2	-1.549	-1.305	3.249	2.264	3.272	-.321	.352	-.038	.096	.324	1.095	-.759	-.504	-.522	-1.198	.718	.074	-.208	.172	-.661	-.312	-.013	.000	
BI_1	-.906	-.978	2.750	2.379	3.649	-.793	.070	-.153	-.071	-.625	.154	-.650	-.224	-.230	-1.395	.234	.235	-.339	.758	-.677	.180	.007	.001	.000

Standardised Residual Covariances (Post-Hoc Model)

	FC_2	V_1	SI_7	SI_6	SRE_1	SRE_2	ReInv_3	ReInv_2	EE_6	EE_5	V_3	V_4	T_2	T_1	PE_4	PE_2	PE_3	BI_3	BI_2	BI_1
FC_2	.000																			
V_1	-.583	.000																		
SI_7	-1.269	.076	.000																	
SI_6	-1.297	.293	.002	.000																
SRE_1	-.771	.520	.670	.311	.000															
SRE_2	.565	1.791	-.118	-.007	.000	.000														
ReInv_3	-.300	.431	-.950	.359	-.054	.147	.000													
ReInv_2	-1.221	.098	-2.001	-.247	.739	-.131	.000	.000												
EE_6	2.522	.423	.536	.622	-1.007	-.069	-.306	-.425	.000											
EE_5	2.231	.516	-.303	-.176	-.991	.045	.056	.139	.000	.000										
V_3	-.735	.061	.404	-.617	.436	-.033	-2.562	-2.505	.877	.899	.000									
V_4	-1.262	-.468	.840	.901	1.791	.909	-2.172	-2.059	.403	.351	.192	.000								
T_2	.393	.559	-1.220	-.687	-.427	2.244	.841	-.238	2.497	3.164	-.580	-.463	.000							
T_1	-.173	.566	.796	.736	.474	2.202	-.351	-.231	.421	1.160	.342	.386	-.044	.000						
PE_4	1.069	.428	.892	.092	.790	.688	1.243	-.145	.866	.675	-1.307	-1.029	1.233	.289	.000					
PE_2	1.110	.457	1.078	-.178	-.679	-.548	.090	-.865	1.651	.645	-.395	.637	1.557	1.343	-.094	.000				
PE_3	.952	.959	.817	.033	-.029	-.023	.857	-.027	-.356	-.866	-.691	.122	1.656	1.054	.007	.034	.000			
BI_3	-.650	2.769	-1.439	-.388	-.985	.416	-.047	-.306	.895	.639	-.952	.571	1.558	.934	.670	-.268	.376	.119		
BI_2	-1.904	1.895	-.847	.044	-.426	.256	.223	.389	.508	.289	-1.535	.157	.519	.025	.459	-.295	.037	.127	.118	
BI_1	-1.457	2.374	-1.199	.244	-.378	.435	-.328	.089	.419	.120	-1.805	-.153	.667	-.056	.862	-.235	.441	.120	.127	.121

Standardised Residual Covariances (Post-Hoc model composite variables)

	SI_IMG	SRE	ReInv	EE	PE	V	TandFC	BI
SI_IMG	.000							
SRE	.000	.000						
ReInv	.000	.000	.000					
EE	.000	.000	.000	.000				
PE	.000	.000	.135	.000	.000			
V	.000	.836	-1.945	.918	.000	.000		
TandFC	-.292	1.809	-.235	.609	.550	.057	.065	
BI	-.058	.353	-.009	.125	.134	-.435	.215	.074

Appendix 22: Pilot Study Reliability Testing

Initial Reliability Scores

Construct	Cronbach's Alpha
Performance Expectancy	.858
Effort Expectancy	.695
Social Influence	.835
Facilitating Conditions	.775
Observability	.868
Trialability	.560
Reinvention	.505
Students' Requirements & Expectations	.753
Students' Learning	.817
Behavioural Intention	.985

Detailed reliability scores before and after deleting items for all constructs

Performance Expectancy					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I would find that using a learning innovation is useful in my job	19.16	34.473	.558	.517	.849
Using a learning innovation would/should enable me to accomplish tasks more quickly	20.08	32.160	.710	.901	.822
Using a learning innovation would/should increase my productivity.	19.96	32.207	.806	.909	.809
If I use a learning innovation, It would/should increase my chances of getting a raise.	21.36	36.073	.357	.408	.890

Using a learning innovation would make it easier for me to do my job.	20.32	28.893	.820	.755	.798
I can reduce my workload if I use a learning innovation.	20.72	31.793	.704	.689	.823

Effort Expectancy					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Learning to use the learning innovation must be easy.	32.84	20.057	.770	.774	.562
I would/should find the learning innovation easy to use.	32.56	22.840	.752	.646	.596
The approach to use a learning innovation must be clear and understandable to me.	32.12	25.777	.515	.628	.649
It would/should be easy to become skilful at using a learning innovation.	32.60	21.167	.724	.724	.581
Using the learning innovation takes too much time from my normal duties.	34.20	32.250	-.191	.240	.802
Using a learning innovation is often frustrating.	34.40	34.750	-.393	.462	.787
The use of the learning innovation do not/should not take much effort.	33.16	21.557	.651	.797	.599
The use of the learning innovation do not/should not require too much time.	33.00	21.167	.588	.786	.611

Social Influence					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
People who influence my behaviour think that I should use a learning innovation.	24.08	26.993	.643	.773	.803
People who are important to me think that I should use a learning innovation.	24.08	27.660	.707	.758	.795
I use/would use a learning innovation because of the proportion of co-workers who use it.	23.88	27.443	.589	.506	.813
The senior management has been/should be helpful in the use of learning innovations.	23.00	28.333	.627	.613	.807
In general, the organization has supported/should support the use of the learning innovation.	22.84	30.557	.436	.523	.835
Using a learning innovation improves/would improve my image within the organization.	23.84	28.640	.537	.501	.821
People in my organization who use a learning innovation have more prestige than those who do not.	24.60	28.750	.570	.561	.815

Facilitating Conditions					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I have control over using any learning innovation I see fit.	16.46	22.085	.627	.475	.706
I have the resources necessary to use the learning innovation I see fit.	16.67	23.449	.578	.593	.725
I have the knowledge necessary to use the learning innovation I see fit.	17.17	23.536	.533	.491	.739
Guidance is available to me in the selection of the appropriate learning innovation that I could use.	16.96	22.389	.653	.630	.699
A specific person (or group) is available for assistance with difficulties in using the learning innovation I chose to use.	17.25	24.717	.378	.564	.795

Observability					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I have seen what others are doing with the learning innovations they are using.	13.83	23.623	.774	.603	.819
The results of using learning innovations are clear to me.	13.75	24.196	.566	.352	**.878**

Learning innovations are not very visible in my organisation.	13.96	26.042	.626	.450	.855
It is easy for me to observe others using learning innovations in my organization.	14.33	24.580	.758	.616	.825
Effective learning innovations in my organisation are disseminated for others to learn from.	14.13	23.158	.768	.641	.820

Trialability					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I've had/I should have a great deal of opportunities to try various learning innovations.	19.25	11.326	.395	.497	.457
I know exactly what I can do to try out various learning innovations.	19.83	12.667	.260	.497	.543
The ability to try a learning innovation before using it is important to me.	18.00	14.522	.121	.206	.614
I am likely to use learning innovations that have been already tested by others and proven effective in my area.	18.13	11.679	.513	.607	.398
I am likely to use learning innovations that I have tested and were proven effective in my area.	17.63	13.114	.369	.549	.483

Reinvention					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I believe that it must be/should be easy to change the learning innovation to do what I want it to do.	16.91	5.039	.078	.244	.573
I am more inclined to use a learning innovation that I am able to change or adjust to suit my needs.	16.68	3.846	.611	.485	.268
I am more likely to adopt and use a learning innovation when I am actively involved in customizing it to fit my unique situation.	16.91	3.420	.443	.351	.302
It is unlikely that I will use a learning innovation that I cannot change or adjust to fit my needs.	17.27	2.589	.257	.173	.579

Students' Requirements and Expectations					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Before deciding to use a learning innovation, it must be clear how it can help me meet or exceed my students' expectations.	16.41	8.444	.357	.366	.786
Knowing about my students' requirements allows me to use an appropriate learning innovation.	16.50	6.643	.737	.654	.600

Using a learning innovation helps me/should help me meet or exceed my students' expectations.	16.59	6.825	.798	.684	.586
The choice of what learning innovation I use is independent of whether it can help me fulfil my student's requirements.	16.91	5.991	.454	.453	.798

Students' Learning					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Before deciding to use a learning innovation, it must be clear how it can improve students learning.	16.86	5.171	.705	.739	.737
The learning innovation I use must/should help improve students learning.	16.82	5.870	.696	.708	.747
Understanding how my students learn best will allow me to use the appropriate learning innovation.	17.27	5.446	.679	.527	.750
I evaluate the learning innovation I use or plan to use to ensure that it enhances students' learning.	17.09	6.563	.488	.385	.834

Behavioural Intention					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I intend to use a learning innovation in the near future.	9.36	12.719	.970	.944	.976
I predict I would use a learning innovation in the near future.	9.23	13.136	.961	.923	.983
I plan to use a learning innovation in the near future.	9.50	12.071	.975	.951	.974

Appendix 23: ML and Bootstrapped Estimations for the Original Model (Model 1)

Regression Weights (ML Estimation) | **Regression Weights (Bootstrapped Estimation)**

Parameter			Estimate	S.E.	C.R.	P	Parameter			SE	SE-SE	Mean	Bias	SE-Bias
BI	<---	PE	0.253	0.042	6.068	***	BI	<---	PE	0.048	0.001	0.253	0	0.001
BI	<---	TandFC	0.14	0.054	2.565	0.01	BI	<---	TandFC	0.061	0.001	0.145	0.005	0.001
BI	<---	V	-0.016	0.062	-0.255	0.799	BI	<---	V	0.072	0.001	-0.017	-0.001	0.002
BI	<---	EE	-0.056	0.033	-1.663	0.096	BI	<---	EE	0.035	0.001	-0.056	0	0.001
BI	<---	SL	0.001	0.096	0.008	0.994	BI	<---	SL	0.124	0.002	0.011	0.01	0.003
BI	<---	ReInv	0.276	0.077	3.565	***	BI	<---	ReInv	0.101	0.002	0.276	0.001	0.002
BI	<---	SRE	0.215	0.109	1.973	0.048	BI	<---	SRE	0.139	0.002	0.206	-0.009	0.003
BI	<---	SI_IMG	0.125	0.04	3.143	0.002	BI	<---	SI_IMG	0.046	0.001	0.123	-0.002	0.001
BI_1	<---	BI	0.994	0.023	43.093	***	BI_1	<---	BI	0.018	0	0.993	0	0
BI_2	<---	BI	0.925	0.023	39.389	***	BI_2	<---	BI	0.029	0	0.925	0	0.001
PE_2	<---	PE	0.943	0.031	30.06	***	PE_2	<---	PE	0.027	0	0.943	0	0.001
PE_4	<---	PE	0.9	0.033	27.647	***	PE_4	<---	PE	0.033	0.001	0.901	0.001	0.001
T_2	<---	TandFC	0.943	0.052	18.306	***	T_2	<---	TandFC	0.07	0.001	0.945	0.002	0.002
V_4	<---	V	0.885	0.053	16.59	***	V_4	<---	V	0.058	0.001	0.886	0.002	0.001
EE_6	<---	EE	0.977	0.041	23.788	***	EE_6	<---	EE	0.042	0.001	0.977	0	0.001
ReInv_2	<---	ReInv	0.893	0.117	7.631	***	ReInv_2	<---	ReInv	0.158	0.003	0.902	0.008	0.004
SRE_1	<---	SRE	0.804	0.071	11.391	***	SRE_1	<---	SRE	0.091	0.001	0.816	0.011	0.002
SI_7	<---	SI_IMG	0.649	0.04	16.284	***	SI_7	<---	SI_IMG	0.042	0.001	0.649	0	0.001
EE_4	<---	EE	0.494	0.033	15.087	***	EE_4	<---	EE	0.036	0.001	0.492	-0.002	0.001
V_1	<---	V	0.795	0.052	15.366	***	V_1	<---	V	0.056	0.001	0.794	-0.001	0.001
SL_3	<---	SL	0.853	0.049	17.251	***	SL_3	<---	SL	0.082	0.001	0.857	0.004	0.002
SL_1	<---	SL	0.89	0.048	18.453	***	SL_1	<---	SL	0.061	0.001	0.893	0.003	0.001
FC_2	<---	TandFC	0.563	0.049	11.468	***	FC_2	<---	TandFC	0.058	0.001	0.561	-0.002	0.001

Appendix 24: ML and Bootstrapped Estimations for the Post-Hoc Model (Model 2)

Regression Weights (ML Estimation)							Regression Weights (Bootstrapped Estimation)							
			Estimate	S.E.	C.R.	P	Parameter			SE	SE-SE	Mean	Bias	SE-Bias
PE	<---	EE	0.213	0.044	4.892	***	PE	<---	EE	0.055	0.001	0.213	0	0.001
PE	<---	SRE	0.445	0.097	4.57	***	PE	<---	SRE	0.104	0.002	0.446	0	0.002
PE	<---	SI_IMG	0.191	0.049	3.873	***	PE	<---	SI_IMG	0.052	0.001	0.19	-0.001	0.001
V	<---	PE	0.226	0.046	4.9	***	V	<---	PE	0.05	0.001	0.224	-0.001	0.001
V	<---	SI_IMG	0.136	0.048	2.848	0.004	V	<---	SI_IMG	0.055	0.001	0.135	0	0.001
TandFC	<---	V	0.65	0.058	11.127	***	TandFC	<---	V	0.069	0.001	0.647	-0.003	0.002
BI	<---	EE	-0.05	0.034	-1.501	0.133	BI	<---	EE	0.034	0.001	-0.05	0	0.001
BI	<---	ReInv	0.259	0.074	3.479	***	BI	<---	ReInv	0.087	0.001	0.261	0.002	0.002
BI	<---	SRE	0.197	0.078	2.519	0.012	BI	<---	SRE	0.083	0.001	0.193	-0.005	0.002
BI	<---	SI_IMG	0.154	0.04	3.858	***	BI	<---	SI_IMG	0.044	0.001	0.154	0	0.001
BI	<---	TandFC	0.171	0.04	4.298	***	BI	<---	TandFC	0.048	0.001	0.171	0	0.001
BI	<---	PE	0.237	0.041	5.733	***	BI	<---	PE	0.048	0.001	0.237	-0.001	0.001
BI_1	<---	BI	0.989	0.02	49.416	***	BI_1	<---	BI	0.017	0	0.99	0	0
BI_2	<---	BI	0.954	0.021	45.666	***	BI_2	<---	BI	0.021	0	0.954	0	0
PE_2	<---	PE	0.951	0.032	29.497	***	PE_2	<---	PE	0.028	0	0.951	-0.001	0.001
PE_4	<---	PE	0.917	0.033	27.433	***	PE_4	<---	PE	0.033	0.001	0.915	-0.002	0.001
EE_6	<---	EE	0.961	0.091	10.54	***	EE_6	<---	EE	0.149	0.002	0.971	0.01	0.003
ReInv_2	<---	ReInv	0.88	0.105	8.36	***	ReInv_2	<---	ReInv	0.113	0.002	0.881	0.001	0.003
SRE_1	<---	SRE	0.66	0.091	7.265	***	SRE_1	<---	SRE	0.11	0.002	0.661	0.002	0.002
SI_7	<---	SI_IMG	0.678	0.042	16.266	***	SI_7	<---	SI_IMG	0.042	0.001	0.678	0	0.001
FC_2	<---	TandFC	0.574	0.05	11.389	***	FC_2	<---	TandFC	0.057	0.001	0.574	0	0.001
T_2	<---	TandFC	1.006	0.054	18.643	***	T_2	<---	TandFC	0.063	0.001	1.009	0.003	0.001
V_1	<---	V	0.807	0.053	15.19	***	V_1	<---	V	0.059	0.001	0.806	-0.001	0.001
V_4	<---	V	0.916	0.056	16.485	***	V_4	<---	V	0.057	0.001	0.917	0.001	0.001