The role of social networking sites in career management skills

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Abstract

The influential work of Rainie and Wellman (2012) posits that use of social networking sites as tools to harness resources of social relations are transformational in context of equality of opportunity in career attainment. This conceptualisation is rooted within social capital theory, whereby personal connections are viewed as potential resources (Lin, 1999) with important benefits for accessing new opportunities and knowledge (Granovetter, 1973, Burt, 1995). Social networking sites offer opportunities for people to network and expand their social capital networks (Rainie and Wellman, 2012), an important career management skill (SDS, 2012). Whilst many consider social networking site usage to be ubiquitous, skill levels required to use the internet productively are unevenly distributed amongst the online population, and closely reflect traditional forms of social and economic inequality (Hargittai, 2008a).

This study investigates utility of SNS as a career management tool as envisaged by Rainie and Wellman (2012), whilst accounting for the second-level digital divide. Enquiry incorporates examination of the relationship between SNS use and career-related outcomes across these key themes. Secondary survey data are utilised exploring the general population, with primary data gathered on mothers of small child, students in further education, and people who have recently been made redundant. These groupings represent people at different career stages, with differing age profiles and different relationships with social media and the internet more generally.

Findings show no consistent benefit to career outcomes associated with SNS use, suggesting that potential benefits are not realised. Although analyses related to the second-level digital divide hint at existence of systematic online inequality, precise identification is not achieved. There is no compelling evidence found that people’s social networking site usage is associated with career-based outcomes.

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Chapter 1: Introduction

Career management skills determine, to a significant degree, our capacity to 'get on in life'. They are the toolkit which we use to navigate the increasingly complex world of modern work that at least in part shapes whether one is able to obtain meaningful employment. Within employment they help define how successful we are. This is why the opportunities for fulfilment offered by social networking sites within the World of work are particularly compelling. This form of networked sociability, it is posited, can help us to harness the resources of socially and geographically disparate actors – regardless of individual circumstances – to achieve our employment potential (Rainie and Wellman, 2012).

The starting point for research contributing to this Thesis is the question 'how useful are social networking sites (SNS hereafter) as a career management tool?' Investigation of this question within the research literature led to the consideration of several groups of social theory which are introduced within this chapter. These can broadly be categorised within two concepts; social capital and the second-level digital divide. These factors mediate and contextualise the central equation testing effects of SNS use on employment outcomes. The definition of career management operationalised is not, however, limited to employment outcomes. Activities contributive to employability are given equal weight.

1.1 Career management skills, social networking sites and inequalities

'Career management skills' is a broad term reflective of the aggregate of influences on our ability to navigate career paths. This includes, but is not limited to, human capital. As defined by policymakers, it includes consideration of social influences, and therefore our ability to harness the resources of motivated others within management of careers.

SNS are distinguished from 'social media' on the basis of networking capability. SNS platforms are take a user profile as a starting point from which she can connect with other users. Profiles, when populated by the user, contain a raft of personal details, likely relevant to the nature of the SNS (e.g. LinkedIn = career information). Connections with other users form a network. Networks built up are articulated through a user contact list, which generally the user's connections can view and 'add' contacts from it if appropriate (Boyd & Ellison, 2007). Well-known examples of such platforms are Facebook, Twitter and LinkedIn. Social media generally do not allow users to construct networks through built-in tools (e.g. 'adding' a friend), and profiles are limited to very basic information. Lack of network-building capacity distinguishes social media from SNS.

SNS are now, for many of us, a mundane and ubiquitous part of everyday life, as routine as using a contactless card to pay for shopping. Although it may be difficult for younger people to remember a time when waking up and checking their Facebook page or Twitter feed was not the norm, SNS are still a relatively new invention. Today's most popular SNS, Facebook (Statista, 2019), began in earnest in 2006 (Facebook, 2006). It has evolved at great speed since to preserve its position at the top of a dynamic global market. Anecdotally, the Researcher remembers being at the vanguard of UK users as an undergraduate in the late 2000's. Then, when checking your 'news feed', you were reading posts made by friends and replies to the posts from their friends. One joined primarily because it felt like abstinence meant missing out. It was an extension of social lives, where interactions on the platform were referenced when chatting in the student union.

Of course, Facebook and other SNS can still be used in this way. But platforms are now much more complex. As SNS companies reached out to powerful actors in order to monetise their product (Hern, 2015; Sadowski, 2016), targeted delivery of information – from advertising to news – became central concerns with regards to consequences for democracies. In the US and the UK, the concepts of 'filter bubbles' (Groshek and Koc-Michalska, 2017) and 'fake news' (Woolley, 2017) became well-articulated explanations for the populist rise evident within results of the US Presidential Election and UK Brexit referendum in 2016 (Woolley and Howard, 2016). Algorithms created to deliver incredibly well-targeted content to users in order to maximise likelihood of profitable 'clicks' inadvertently created news bubbles which users could insulate themselves within. Lack of exposure to diversity of thought, or balanced reporting within a relatively unregulated environment contributed to political polarisation.

This leads us to the influential work of Lee Rainie and Barry Wellman. Their 2012 book *Networked: The new social operating system* was well-received in academic circles. Prominent internet and social capital scholars such as Manuel Castells, William Dutton, Howard Rheingold, and Ronald Burt amongst others have written endorsements of the book (MIT Press, 2019). Its central assumption is that social capital – defined as access to social resources (or connections) – is much easier to accumulate with the advent of SNS. Traditionally, access to a network of potentially valuable contacts is mitigated by a range of factors: temporal, geographical, financial, to name some. SNS are the culmination of innovations throughout the 20th and 21st centuries that has worn away these barriers. Connections can now be formed and maintained with individuals around the world from the comfort of one's home. Rainie and Wellman (2012) posit that with the requisite amount of work, anyone can build a network of acquaintances that cumulatively possess a wide range of knowledge and capabilities. This network can be activated in times of crisis, or to help people get on in life. Career management is an area that the authors explicitly identify where access to social resources can result in more beneficial outcomes, building upon established social capital literature (e.g. Granovetter, 1973; Lin, 1999).

Rainie and Wellman's (2012) book is a compelling story of how new technologies can be a transformative force for personal attainment. Their observations regarding barriers traditionally inhibitive to building and maintaining a significant network of social resources imply as much. Well-resourced networks are no longer a preserve of more privileged groups. However, reading the book particularly as a sociologist, the scope of analysis appears simplistic and evidence drawn upon is lightweight. Anecdotal case studies of individuals who seem like talented networkers are accompanied by statistics that correlate heavy internet, smartphone and SNS usage with expended social networks. Case studies of less exceptional individuals, or consideration of cause-and-effect within the statistical relationships are not given corresponding weight. Are heavy users of SNS skilled networkers anyway? Is this why they spend more time on SNS? Science probing the theoretical positive relationship between SNS use and greater career attainment should be rigorous to fully test ideas that have become quite widely accepted. Since Rainie and Wellman's (2012) research, platforms have become more complex to interact with and more ambitious in scope, adding further urgency for the case of more rigorous scientific enquiry.

Another issue raised within the question of cause-and-effect is revealed through reviewing related literature. The 'second-level digital divide' refers to the spectrum of abilities distributed amongst internet users (Hargittai, 2008a). Research within this area finds that internet users, unsurprisingly, are not a homogenously capable bloc. People online use the internet for a range of vocational and avocational purposes, and outcomes differ from similar uses. Outcomes differ because of variation in capabilities of users. Variations in uses and capabilities are explained by a range of factors. However, research that focuses on vocational – or productive – internet use identifies educational attainment as the best-performing predictor of such uses (Robinson *et al*, 2003; Hargittai and Hinnant, 2008; Wei and Hindman, 2011). Hargittai (2008a) likens this educational effect within new media to that within old media. When the same information is given to people of a range of abilities and educational attainments, the ability to use it productively – to one's advantage – lies with more capable individuals. Or, in other words, Hargittai notes, offline inequalities are reproduced online.

Further nuance to add to the equation is identified within a review of social capital literature. Rainie and Wellman's (2012) thesis builds upon the concept of 'the strength of weak ties' first proposed by Mark Granovetter (1973). Whereas 'bonding social capital' is associated with strong ties (or people one is close to), 'bridging social capital' is held within looser-knit social relationships, or weak ties (Putnam, 2000). The main benefits of bonding social capital are mostly related to emotional support, but bridging social capital is more likely to give access to original information that is in turn more likely to provide opportunity within career management (Lin, 1999). Research gauging career management benefits (most often employment outcomes) reveals that social position affects both access to weak ties, and benefits derived from use of weak ties (e.g. Lin *et al*, 1982; Moerbeek *et al*, 1995; Torres and Huffman, 2002).

Therefore, a review of research literature associated with the ideas espoused by Rainie and Wellman (2012) reveals undermining stratification effects with regards to the central tenets of their Thesis – social capital and the internet or SNS use. This Thesis explores the role of SNS in career management, taking into account these nuances of stratification in order to address gaps in Rainie and Wellman's influential work.

1.1.2 Research Questions

The following research questions are derived from a review of literature of theoretical and practical implications within the question of utility of SNS within career management (Table 1.1).

A: Does SNS use benefit career management?	**B: Who embraces the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	B1) Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	B2) Who uses the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	B3) Is there an uneven distribution of positive, career-outcome effects from weak tie social capital?

Table 1.1: Thesis research questions.

1.2 Thesis structure

The following section provides a brief overview of the analytical strategy operationalised within this study, and an introduction to following chapters. Thesis research questions follow the literature review in Chapter 2 (*2.7.2*).

1.2.1 Analytical strategy

A quantitative analytical strategy is employed within the study, which aims to create impact through generation of findings representative of the UK population, with focus on Scotland.

Data analysed is composed of two UK-level publicly available social survey data sets, and three primary survey data sets which oversample Scottish residents. Of the two secondary data sets, one is a large UK household panel survey with indicators covering a wide range of topics (Understanding Society), and the other a relatively small data set containing indicators focused on internet use (Oxford Internet Surveys). Primary data sets are grouped by a particular context, aiming to capture challenging career contexts as compelling sites of analysis of career management. These contexts served as parameters for recruitment; further education students at around the time of completing a course, mothers of young children, and individuals made redundant from their employment. Average sample ages reveal coverage of career stages across the working life course.

Although data analysed is composed of quantitative indicators, literature informing direction of analysis is not limited to quantitative studies. Literature from within sociology and beyond is considered on the basis of relevance to the study. One of the greatest challenges in creating this Thesis was the reduction of relatively broad social theories into measurable statistical indicators. The majority of results presented are from regression modelling.

1.2.2 Chapters

Chapter 2 provides a detailed and sequential summary of literature reviewed that helps both explain the theoretical efficacy of SNS use within career management, and inequality-related factors which should mitigate utility for some. This leads to a statement of Thesis research questions and literature 'gaps' where this work contributes original research.

Following this, Chapter 3 provides detailed commentary on methodological aspects of conducting this research. Sections dedicated to each data source used (each the topic of one analysis chapter) are cover finer points relating to the data and how it is analysed.

Chapter 4 presents analysis of Oxford Internet Surveys data. A subsample of internet users is selected with reference to specific interest in the 'online' population generated through the relevance to the Thesis of the second-level digital divide. Specific analytical attention is given to identification of population markers of differential uses of the internet as a result of the data being particularly rich in indicators of online behaviour.

Next, Understanding Society analysis is presented in Chapter 5. Again, a subsample of respondents is isolated. These respondents are identified as unemployed and actively seeking employment. Indicators of different types of job-search techniques and SNS use are used to predict outcomes relating to job attainment and job quality of employment at a later date (data use spans multiple waves of the survey). Thus, the efficacy of social capital use in job seeking, with and without the use of SNS as a medium is tested in context of employment outcomes.

Chapters 6-8 present results from analysis of primary data, each chapter corresponding to a case study population. These are presented in chronological order with reference to the working life course. In Chapter 6, further education students' optimism with regards their future career operationalised as the main context within which indicators relating to SNS use are tested for utility. Chapter 7 contains results of a similar theme from analysis of data pertaining to mothers of young children. Respondents made redundant from employment are the subject of Chapter 8. Job attainment amongst this sample of active jobseekers is the main theme of analysis. All primary data is subject to analyses which test the influence of weak ties specifically within career management, which was not possible with secondary data.

Finally, Chapter 9 concludes the Thesis, summarising and discussing results of the research. Conclusions are made with reference to research questions and wider literature bodies, as well as impact outside of academia.

Chapter 2: Literature Review

2.1 Introduction

The starting point of this literature review, which synthesises evidence pertaining to the utility of SNS use within career management, is the concept of career management skills (CMS). Broadly defined, the concept refers to the abilities of individuals to navigate the world of work (SDS, 2012). Adoption of the concept is part of a push by several European and English-speaking nations to abandon traditional, inflexible, models of career guidance in favour of adopting models which place the individual's requirements at the core (Sultana, 2012; Hooley *et al*, 2013). The refreshed models include recognition of the importance of digital competence and of social connections in shaping careers paths.

Social capital denotes access to resources embedded within one's social relations, or ties (Lin, 2000). A body of theoretical and empirical evidence (Granovetter, 1973; 1974; Lin and Dumin 1986; Lin 1999; Rainie and Wellman, 2012) asserts that embedded resources that exist in social relations characterised by weak social ties – as opposed to strong – are often the most valuable for an individual to develop her career.

According to one strand of social capital theory (e.g. Lin, 1999), this is due to the tendency of an individual's strong ties (close friends and family) to be part of densely-knit clusters in network theory, representing closed circuits of information. Weak ties, on the other hand (acquaintances), are connections that are not a part of ego's dense clusters, but can reasonably be expected to be part of someone else's. Therefore weak ties can act as conduits of *original information* for ego, brought from their own densely-knit clusters of strong ties (Burt, 2004).

In the context of careers this information can occur in the form of hearing about a job from a weak-tie (Lin *et al*, 1978), or by gaining opportunities to learn new skills and develop existing ones via weak ties (Rainie and Wellman, 2012). Skills that determine an individual's employment value or prospects are referred to as human capital when aggregated together (Becker, 2008). The ability of an individual to improve their human capital forms a key component of their CMS.

Forms of capital of particular interest presently – social and human – do not exist in vacuums. They overlap and interact with each other, and with other forms, such as cultural capital (Bourdieu, 1986). The ability to manage social capital well is widely acknowledged as a core component of managing a successful career (De Janasz *et al*, 2003; Forret and Dougherty, 2004), and 'networking' is indeed included as a key component of lifelong learning in Scotland's strategic framework for career management skills (Skills Development Scotland, 2012). Therefore social capital management in itself is a component of human capital, as well as acting as a mechanism to leverage information that contributes to human capital improvement.

There is a growing academic research interest in the potential of online social platforms to develop and maintain social capital through weak-tie relationships (Hargittai, 2008c; Steinfield *et* al, 2008; Vitak and Ellison, 2012). Perhaps the most widely disseminated of these works was written by Rainie and Wellman (2012). The latter work views SNS as transformative tools within career management, through mitigation of barriers traditionally inhibitive to the development and maintenance of valuable weak tie networks.

Rainie and Wellman's (2012) work however ignores a body of research centred around the concept of a second-level digital divide amongst internet users. In context of widespread internet connectivity in North America and Europe, such research shows that a spectrum of skills exists among internet users, predicted particularly well by educational attainment (Hargittai, 2008a; Wei and Hindman, 2011). The implication of the second-level digital divide for career management is that digital competency should impact on users' ability to utilise SNS in the way that Rainie and Wellman (2012) envisage. The replication of socioeconomic inequalities within the online sphere suggests that SNS are not a transformative tool for equality of opportunity within career management.

2.2 Career Management Skills

'Career management skills' is a broad term that refers to the aggregation of personal characteristics and abilities that enables an individual to 'plan and pursue life, learning and work opportunities' (Skills Development Scotland, 2012; p. 1). The concept places the individual at its core, and advocates equipping citizens with the tools required to effectively manage their career through informed choices and 'lifelong learning' (i.e. education/training throughout working lives). Its advocates assert that in flexible and changing labour markets individuals need to be equipped with a range of tools to effectively manage their careers. This philosophy differs from more traditional methods of career advice and education which focus more on the making of vocational choices, in that it acknowledges that a range of qualitative factors influence the direction of careers (Hooley *et al*, 2013).

With the concept of CMS gaining traction around the world, several countries in Europe (Sultana, 2012) as well as the US, Canada and Australia (Hooley *et al*, 2013) developed strategic frameworks designed to implement their versions of the philosophy at national levels. Scotland produced its own version, developed by Skills Development Scotland (2012), and it is within this context that the present study is funded to contribute impact towards CMS delivery in a digital age.

The CMS Framework for Scotland asserts that the key competencies required for effective self-directed careers management fall into four categories; 'self, strengths, horizons and networking' (pp. 8-9). The concern of the present study lies with the fourth category; specifically in the study of how people can 'use information and relationships to secure, create and maintain work' (p. 9) using the online sphere. A central concern of this study then, is the role of SNS platforms designed for the purpose of social networking.

Although the CMS Framework for Scotland does not explicitly mention the importance of IT skills in being able to pursue networking strategies in the digital age productively and effectively, the notion of 'digital competence' has been placed at the heart of many European frameworks (Sultana, 2012). This literature review maps how bodies of empirical work indicate that digital competence should be a mediating factor within the success of digital networking.

2.3 Forms of Capital

Capital is a term that, in economic discourse, has a relatively simple meaning, referring to 'assets that yield income and other useful outputs over long periods of time' (Becker, 2008). This could refer to money in a savings account, an investment in the form of shares, or agricultural machinery owned by a farmer. It is a catch-all term to denote a tangible asset that is capable of providing a return for its owner.

Other forms of capital are detailed in the fields of economics (human capital) and sociology (social and cultural capital) that attempt to describe specific mechanisms and nuances that are contained within the broad meaning of capital. The importance of this diversification of definition is captured by Pierre Bourdieu (1986):

> 'It is in fact impossible to account for the structure and functioning of the social world unless one reintroduces capital in all its forms and not solely in the one form recognised by economic theory' (p. 83).

It is likely inaccurate to accuse all economists of such reductionism, given 'human capital' had gained a large influence in economics long before Bourdieu penned that quote (see Johnson, 1960 and Becker, 1964 for two examples). Social capital has now gained traction within economics too (for examples see; Glaeser *et al*, 2002; or Dasgupta, 2005). But Bourdieu does capture the necessity of understanding how capital operates, effects of use, and how it is reproduced through a definition of its gradations first. Consequently, aspects of capital theory which provide theoretical guidance to this study are discussed, with particular reference to definitional divergences which effect study design.

The collection of skills and knowledge which effects individual capacity to succeed in employment are referred to by economists as human capital (Schulz, 1961), and thus must be considered as central within the context of CMS. It is labelled as such, according to Becker (2008) 'because people cannot be separated from their knowledge, skills, health or values in the way they can be separated from their financial and physical assets'. Human capital is fundamentally described in economic terms, embracing the central concept of 'capital as investment (e.g., in education) with certain expected returns (earnings)' (Lin, 1999; p. 29). In similarity with capital then, human capital is a tangible, investable entity that is usually expected to yield capital returns. This conceptual clarity enables researchers to isolate socioeconomic variables in order to empirically quantify and measure investments and returns.

Whilst it is possible to invest in and yield returns from the 'human' capital, it is also possible to invest in and yield returns from the 'cultural' and the 'social' capitals. Another form of capital, described by Bourdieu (1986, 1990; Bourdieu and Passeron, 1977) is cultural capital. Cultural capital refers to a desirable collection of cultural knowledge, tastes and possessions held by an individual that is emphasised by symbols (Field, 2003). Such symbols contain cultural capital, and is one of three forms in which it can exist, termed the 'objectified state' (Bourdieu, 1986). Symbols include books, pictures, instruments and works of art. The second is the 'embodied state': an internalisation of culture reflected in attributes such as accent or taste. The third is conferred in the guise of a formal qualification; the 'institutionalised state', which infers credentials such as having received a university education.

Bourdieu saw the power of cultural capital as being reinforced by another form of capital; social capital. Capital-rich elites, for Bourdieu, harness the power of their social connections with family, friends and acquaintances (of similar socioeconomic standing) to exert 'a multiplier effect' on the capital that they 'possess in their own right' (1986; p. 89). Social capital enables the pooling of capital resources amongst a social network, providing a greater aggregate than the individual alone has available. According to the principle of homophily – that socially, 'similarity breeds connection' (McPherson *et al*, 2001; p. 415) – elites have an especially generous pool of resources available to them, which along with symbolic meanings helps to preserve the hierarchical status quo. Furthermore, those who put in an 'unceasing effort of sociability' (Bourdieu, 1986; p. 90) can be 'sought after for their social capital', as they become 'well known' and ultimately, 'worthy of being known'.

Drawing a parallel between the forms of capital discussed presently, key themes to emerge from Bourdieu's analysis are the ability to *invest* in both cultural capital and the size of one's social network in order to gain a *return* in the form of access to greater amounts of forms of capital. Whilst Bourdieu refers often to the macro, net-effect of cultural and social capital for society – the reproduction of hierarchical social orders – he simultaneously identifies ways in which capital can function on an interactional level; through shrewd investment and management of cultural and social capital the individual can generate 'highly productive' (p. 90) outcomes. It should be added, however, that highly productive outcomes do not all necessarily take the form of capital itself – or one of its physical derivatives, money. Utility theory in economics (for examples see Marshall, 1890; or Samuelson, 1938) explains why some people may for example, study a course at university as an investment with expected non-monetary returns. Utility theory helps economists factor human rationales such as happiness and satisfaction into motivations for capital generation.

Ways in which these capital forms interact, or are dependent on one another, can be sketched out, although it is difficult to quantify these relationships. Bourdieu's work implies linkages between economic capital, human capital, cultural capital and social capital through how elites use these assets to maintain a preferential position within the social hierarchy. Social capital itself is seen by Bourdieu as an individual (can be used to multiply other forms of capital) and as a structural (preserves the status quo) concern.

2.3.1 Forms of social capital

A review of other key theorists operating within the space of social capital highlights a lack of definitional consensus over the meaning of the concept, and consequently relevance to the subject matter of this Thesis. This sub-section serves to define and justify the pathway within social capital theory that this study follows and contributes towards.

Robert Putnam (1996; 2000) largely focusses his analyses of social capital at the macro level. In the context of 'civic engagement', Putnam defines social capital as 'features of social life – networks, norms, and trust – that enable participants to act together more effectively to pursue shared objectives' (1996; p. 34). Basing his analysis in the U.S., Putnam views a perceived decline in patterns of civic engagement - such as political, civic and religious participation - as being symptomatic of an aggregate decline in social capital at community and national-levels (2000). A lack of shared values and cohesion at community and national-level has resulted in Americans no longer being able to work together in the pursuit of common aspirations. However valid Putnam's findings may be though, his operationalisation of the concept of social capital can be considered problematic in the sense of its broadness. The use of one term in an attempt to capture an array of qualitative sociological factors inevitably leads to degrees of overlap with other concepts. Community and (collective) identity, as identified respectively by authors such as Cohen (1985) and Bauman (2000) are two such concepts that refer to the many sociological themes - such as societal cohesiveness, shared experience and shared values - that are encompassed by Putnam's definition of social capital.

James Coleman (1988; 1990) also places emphasis on collective attributes such as norms, trust and closure (connectedness within a social structure/network) as being important facets of social capital. He, like Bourdieu, highlights how the individual rationally uses their social capital to gain access to further resources:

> 'If we begin with a theory of rational action, in which each actor has control over certain resources and interest in certain resources and events, then social capital constitutes a particular kind of resource available to an actor' (1988; p. S98).

The specific resources denoted by Coleman were those which belong to human capital, who in common with Bourdieu saw interactions between forms of capital. Also like Bourdieu he identifies the family as being especially important in enriching children with advantageous attributes via socialisation. Without the presence of social capital embedded within the relations between parent and child, he argued, then the amount of human capital held by parents is 'irrelevant' as the tools or motivation to complete this enrichment process are not available (p. S110). Whilst families are undoubtedly an important part of our social networks (especially in formative years), these networks are not confined to connections with kin. Christakis and Fowler (2009) for instance, show how the size and scope of our personal social networks ensure that important social transactions reach far beyond the family unit.

Coleman's (1988) analysis of social capital also stretches beyond access to resources through individual and family units. Like Putnam, he was also interested in social capital on a more macro-scale. Investment by individuals in social capital is an investment within the social structure, which in turn is where capital lies. Such investments benefit the social structure. For example, if an individual attends meetings of a community organisation – thereby participating in a new avenue of networking – the organisation also benefits by having access to the new resources brought by the individual. As with Putnam's work on social capital, Coleman's ideas are expansive, and difficult to operationalise within research.

Nan Lin (1999) argued for a tightening of the definition of social capital because of these definitional divergences to enable researchers to better capture measurements of the concept in order to link it to individual-level outcomes:

> 'Divorced from its roots in individual interactions and networking, social capital becomes merely another trendy term to employ or deploy in the broad context of improving or building social integration and solidarity' (p. 32).

A similar critique of the conceptually broad nature of cultural capital was offered by Zimdars *et al* (2009), in the difficulties they experienced in identifying indicators of the concept in a higher education dataset. Therefore, in order to be able to quantify and measure indicators of social capital the present study operationalises the concept of social capital at an interactional level.

Social capital, therefore, functions as both a form of capital in its own right and as a mechanism to acquire other forms of capital that are embedded within, or facilitated by, social relations. Cultural capital does sometimes require social capital to be transmitted from one individual to another, but the concept is not clearly enough defined via empirical study to justify inclusion as a theoretical driver in the present context. Human capital, in a career management context, is an important consideration. Its relationship with social capital is therefore considered at the interactional level; contacts may transmit human capital directly to one another (e.g. advice on writing a CV), or may provide additional information that allows one to improve their human capital (e.g. referral to an organisation that provides CV-writing advice).

The functions and perceived benefits of interactional level social capital are quantified through its effect on (or association with) career-based outcomes. Examples include the frequency of which jobs are secured through a social contact (for examples see: Langlois, 1977; Ericksen and Yansey, 1980; Volker and Flap, 1999), or the effect of gaining a job through a contact on wage levels (For examples see: Green *et al*, 1995; Elliot, 1999; Torres and Huffman, 2002).

The relationship between human capital and social capital is also an established study topic within the literature. Ferguson *et al* (2016) examine conditions in which social capital can activate the accumulation of human capital amongst expatriate Lithuanian communities. Kobayashi *et al* (2015) analyse the interaction of both forms of capital in relation to the length of time in the respondents' first job. Rainie and Wellman (2012) draw explicit links between social capital generated and maintained through the internet, and the acceleration of human capital accumulation. Their conclusions are considered particularly important to this Thesis, due to the impact it achieved. It has been recognised via awards from bodies such as the American Sociological Association and has received praise from notable academic authors - Manuel Castells, William Dutton and Ronald Burt, for example (MIT Press, 2019).

2.4 The Strength of Ties in Network Theory

Research operationalising interactional level social capital has involved many authors placing emphasis on the importance of the strength of ties in social networks – particularly in context of positive employment outcomes generated (Granovetter, 1973; Lin and Dumin, 1986; Lin, 1999). A 'tie' simply denotes a relationship between 'nodes' – which in network theory can refer to individuals, organisations or even countries (Borgatti *et* al, 2013). Presently, ties refer to social relationships between individuals. Interpersonal ties are commonly classified into two categories – strong and weak (e.g. Granovetter, 1973; Kramarz and Skans, 2014; Gee *et al*, 2017). A strong tie refers to a relationship in which interaction is commonplace and emotional bonds often durable - usually amongst family or close friends. A weak tie is characterised by more loosely-knit relations such as acquaintances, where frequency of interaction is not common; or work colleagues with whom interaction is common, but emotional attachments are weak (Burt, 1995).

'Latent' ties are less commonly referred to in academic literature, but help provide greater clarity of definition to the concept of weak ties. A latent tie is a potential tie that has yet to be activated (Haythornthwaite, 2002). This can refer to individuals that you have the potential to come into contact with; for example a member of the same rowing club as you, someone who works in the same office, or a friend of a friend – that you have yet to start up a relationship with. Robin Dunbar (2010) suggests that humans' ability to maintain ties with large networks is cognitively limited to 150, which would imply all potential and actual ties beyond this number may be latent.

Putnam (2000) identifies two different types of social capital that correspond to the two types of tie. Strong ties produce 'bonding' social capital, whilst weak ties yield 'bridging' social capital. Both types of social capital yield different resources, and are therefore typically associated with different outcomes. Bonding social capital is most likely to produce emotional benefits for the individual (Field, 2003), which in turn reinforces bonds within a tight-knit social group (Putnam, 2000). The act of accessing such resources are referred to as 'expressive' actions (Lin and Dumin, 1986). Benefits related to bridging social capital are more likely informational, such as hearing about a job vacancy (Granovetter, 1973) or receiving advice in the process of applying for a place on a course in Higher Education (Rainie and Wellman, 2012). Accessing bridging social capital is referred to as an 'instrumental' action (Lin and Dumin, 1986). The perceived benefits of bridging social capital can thus be separated into two categories in relation to CMS; direct career benefits (social support leading directly to a job) and indirect career benefits (social support leading to enhanced human capital).

In social network theory, informational resources are most common and useful when embedded in weak ties that provide 'bridges' between 'structural holes' – providing access to new forms of information from different social groups that are not available in relatively homogenous strong-tie social clusters (Burt, 2004).

The importance of bridges emerges from the tendency of people to form relationships with like-minded others. Social network theory visualises social relations as nodes connected to one another, with clusters of nodes emerging which represent tightly knit groups of relations, who often have similar norms and values emerging from shared life experiences. Whilst membership of these groups provides bonding social capital, the similarity of the individuals within ensures a relative lack of original information passes through the group – 'the network becomes an important screening device' (Burt, 1995; p.14) for opportunities, due to its inherent homogeneity. In order to gain access to new and potentially rewarding opportunities such as new jobs, new funding pools inviting proposals, or new projects requiring leadership (p. 13), one's position within the wider networked social structure has a significant impact. The more bridging connections a person has that connect to different social clusters, the more likely they are to hear about these new opportunities, and take advantage of this nonredundant information.

Before moving on, it is important to make a clarification regarding the utility of strong ties. Although theoretically weak ties have better access to potentially advantageous information within career management, other factors render the picture a little more nuanced. Strong ties are logically more motivated to help an individual than weak ties, and therefore have a certain role to play within career management (Granovetter, 1983). The effectiveness of relative tie types is also determined by a number of factors, more or less representative of position within the social hierarchy. Stratification of benefits associated with weak ties is returned to in greater detail in *2.4.2*.

A further clarification addresses how Granovetter's original 'strength of weak ties' theory has been applied in subsequent academic research. Two broad approaches have been followed, characterised by how the strength of a tie is defined. One approach is favoured by network scientists, who define the strength of a tie according to algorithmic logic. This is based upon network data which quantifies exchanges between individuals, groups of actors, organisations, or even nations. The quantification of exchanges is often the basis for distinguishing between types of tie.

The other approach is that taken in the present study. It is generally favoured by social scientists (e.g. Griffiths and Lambert, 2015) who define tie types according to non-algorithmic factors discussed within relevant analysis chapters in this Thesis.

2.4.1 The Strength of Weak Ties in Empirical Research

Since the early works of authors like Mark Granovetter (1973; 1974) scrutinising the perceived informational advantages of greater access to weak ties within the social structure, a significant body of research has been published within the substantive area. Despite this, Granovetter's assertions that a) receiving job information from ties is more beneficial than not using social capital in search of employment and b) that weak tie information provides greater utility than strong tie information, have not become widely accepted. Both of these hypotheses have received mixed support when empirically tested.

Nakao (2004) analysed the US General Social Survey (GSS), finding that social capital in addition to human capital was associated with greater status attainment (employment) outcomes. Cappellari and Tatsiramos (2011; 2015) found that personal network quality in terms of having a greater number of friends that are employed had a significant, positive effect on an individual's likelihood to be employed themselves with analysing British Household Panel Survey (BHPS) data. Similarly, Bonoli and Turtshci (2015) discovered that a greater number of work-related personal contacts increases likelihood of an early exit from unemployment, upon interrogation of Swiss data. However, upon a comparison of the use of informal (obtaining through a contact) versus formal (for example, responding to an advert) methods of getting a job from a survey of Swiss graduates, Franzen and Hangartner (2006) found that informal methods resulted in a 5% wage penalty compared to formal methods. Elliot (1999) also reports significantly lower earnings associated with use of informal methods to obtain employment.

Rost (2011), studying innovation within networks, where Burt (1995; 2004) identifies weak ties as being advantageous for hearing about 'good ideas', concluded that the impact of weak ties is overestimated in some research and that strong ties were vital to the network as a whole. Other studies demonstrate the utility of strong tie use at the individual level (e.g. Krackhardt, 1992; Kramarz and Skans, 2014).

Murray *et al* (1981) found that more academics at one Canadian and one US university found jobs through strong, rather than weak ties. Granovetter (1983) criticises their findings through the fact that 80% of jobs analysed were the first academic positions of the respondent. He points out that Ph.D. students have relatively undeveloped networks, and typically rely on supervisors or mentors for help in getting a job – positions of relatively frequent interaction. Therefore, Murray *et al.*'s (1981) contextualisation of their findings as evidence against the power of weak ties in employment contexts is not appropriate, given the atypical nature of first academic positions, and use of a sample unrepresentative of academic workers.

Granovetter's findings lend greater support to the idea that weak ties are more helpful for getting jobs than strong ties. His 1973 study of a random sample of professional, technical, and managerial workers based in Boston (US) found that 56% of respondents who found a job via informal channels used a contact whom they only spoke to occasionally, versus 17% of respondents whose contact they spoke to often. In a later publication (1974) Granovetter found greater job satisfaction reported amongst respondents who gained a job through a weak tie too, as well as longer periods of unemployment associated with strong ties (as opposed to weak). In addition, he cites (1973; p. 1371) earlier studies from Shapero *et al.* (1965), Brown (1967), and his Ph.D. Thesis (1970) that show similar patterns of positive weak-tie-employment outcomes amongst blue-collar workers.

Variation within findings studying the utility of social capital use, and the strengths of respective types of ties within career management is likely caused by a range of factors such as study design of definitions of important concepts. A body of research highlights another factor – context. Many of these studies focus on position within the social hierarchy in relation to social capital, described in the next section.

2.4.2 Social capital, tie use, and stratification of benefits

Although the advantages of social capital use via informal job-seeking methods, and the relative merits of the use of bridging social capital with informal methods are relatively uncertain, what is quite clear is that outcomes associated with the use of social capital in employment contexts vary along lines of occupational class, inherited privilege, gender, and ethnicity. Characteristics associated traditionally with relative disadvantage within employment markets – or structural inequality – are also associated with lower social capital, less access to weak ties, and worse outcomes when social capital is used within career management.

Borlagdan (2015) employed a qualitative design from a Bourdieusian perspective, using a sample of 21 year-olds transitioning from education to employment that emphasised the variable dynamics of social capital amongst the UK social class spectrum. Borlagdan (ibid) found that social relations have significant power in shaping these career transitions, and that structural circumstances produced both negative and positive social capital. Negative social capital was found primarily amongst the students from disadvantaged backgrounds, who struggled to conceptualise a successful navigation of this transitional period – views which were reinforced socially amongst their homophilous social groups. A more optimistic view was shared by the students from more advantaged backgrounds.

Other works have also focused on distributions of ascribed social capital afforded to young people. Verhaeghe *et al*. (2013) used three measures of inherited stratification as predictors of whether new labour market entrants stated that they would be able to receive support in getting a job from a family member – the latter being a measure of social capital via a resource generator instrument. The researchers found modest, but significant linear effects amongst all stratification predictors, concluding that ascribed social capital can make a difference to young labour market entrants transitioning into employment. Moerbeek *et al.* (1995) used father's occupation as an indicator of social capital when it was mentioned by the respondent as the social contact that helped them to secure a job. This predictor exerted a positive and significant effect on the statuses of both first, and current/last jobs for men and women. Lin *et al.* (1981) however, did not find this continuing ascribed effect of social capital beyond the respondent's first job. Their analysis revealed that for the first job, relatives were the most used contact when securing a job via informal methods. Then the importance of familial contacts diminished over time, as constructed networks began to replace ascribed ones.

A gender divide has also been identified with regards to social capital. McPherson and Smith-Lovin (1982) discovered a gender split in terms of the size of voluntary organisations that respondents were members of. Men were connected mostly to large organisations, often linked to economic institutions, whilst women tended to be connected to smaller, more peripheral, community-level organisations. This led them to conclude that men had greater potential to nurture weak-tie relationships with more influential actors. Van Tubergen and Volker (2015) measured social capital in the Netherlands via a position generator – denoting access to contacts within the occupational strata. Whilst social capital increased with age and education, levels remained consistently lower for women, because of less diversified networks. Another study, situated within an occupational context by Lutter (2015), also found that women have had less access to weak ties in the workplace on a longitudinal basis. Women's project teams tended to be more close-knit and homophilous than men's. Hamm *et al.* (2013) find evidence from the US that the principle of homophily actively perpetuates existing structural disadvantages for women in terms of access to informational social capital – because people embedded in labour markets are more likely to give informational support to those of the same gender (and race). Finally, earlier research by Torres and Huffman (2002) suggested that the interaction of being female with social capital levels resulting in a disadvantage in employment was proxied through human capital (years of work experience), using annual earnings as the dependent variable. Although it must be noted that this research is confined to professional, technical, and managerial workers – which are often portrayed as sectors in which relatively more men than women find work (for example, see Charles and Grusky; 2005).

The finding of the reinforcement of structural inequality created by racial disadvantage via the proxy of social capital identified by Hamm *et al* (2013) is supported by Verhaeghe *et al*'s (2015) longitudinal study regarding labour market entry in Belgium. They too find significant ethnic differences in social capital levels, which are ultimately explained by the socioeconomic deprivation of minorities within their models. Green *et al*'s (1995) earlier work applies William Julius Wilson's theory of urban poverty in the US as the ultimate cause of social isolation (lack of heterogenous ties) – unskilled migrants often cluster together in US urban areas defined by poverty, in a process known as 'ghettoisation' (Wilson, 1996). Wilson points out that residents of ghettos often live in a homophilous culture of low education, skills, and unemployment, and lack successful role models. Green *et al* (1995) discovered that jobs found through contacts yielded lower average earnings for ethnic minorities, which they concluded were the consequence of structural disadvantage proxied through social capital.

Friedland (2015) synthesised works of key urban theorists to argue that physical space shapes the social networks of individuals. With regards to employment outcomes, Elliot's (1999) analysis of job-search techniques on earnings - pegged to spatial data - provides further support to the interaction of place and race producing negative social capital. Elliot found that whilst there was no difference in the efficacy of using contacts to acquire a job for people from poor and nonpoor areas, if a white contact from outside a poor neighbourhood was used to acquire a job, average earnings were significantly higher than if a non-white contact was used from a poor neighbourhood.

The above evidence connotes a stratification in the effects of weak-tie social capital by education, which was explored by Kramarz and Skans (2014). They looked at the effects of both strong and weak ties on earnings, by education level using data from the 1980's. They find that whilst for all education levels getting a job through strong ties was associated with higher earnings, the disparity narrowed in a linear fashion through educational levels. For the lowest educated sample members, use of strong ties resulted in 6 times better wages than use of weak ties, but for university graduates the strong tie effect was reduced 2 times higher on wages. Previous research by Ericksen and Yansey (1980) found a similar linear predictive effect from the interaction of social capital and education level. However, their data showed a wage boost from the use of weak ties for high school graduates (modest) and above (larger), compared to a wage penalty amongst those with a low level of education, whilst the use of strong ties had no consistent effect.

As an aggregate, the body of literature assessing the theoretical value of weak tie informal job acquisition methods provides mixed evidence. There is probably stronger evidence for this argument than against it, and it is apparent that social capital interacts with socioeconomic position, gender, and ethnicity to produce an uneven distribution of social capital amongst the population. Nan Lin (2000) refers to those constrained by largely structural social capital inequality as victims of a (social) 'capital deficit', with the parallel concept of 'return deficit' (p. 786) denoting any disparity in outcomes associated with the expenditure of social capital.

However, these employment-related outcomes in theory do not necessarily follow the same trajectory through social privilege as social capital deficit. According to Lin *et al* (1981), the instrumental activation of weak ties can be so effective because of the 'prestige principle' – the tendency to contact those in higher positions within the social structure. This makes sense as in a job search scenario, it would arguably be the rational thing to do. For example, if you are looking to gain employment within a sociology department and had two weak ties employed within this context – but in different hierarchical positions – the logical choice (on the face of it) would be to request the help of the most senior.

It also follows logically that if instrumental actions are guided by the prestige principle, then weak ties should produce better outcomes for people with a lower starting position within the social structure, provided those at the bottom have access to prestige (or relative prestige). The concept works due to what Lin and Dumin (1986) refer to as a 'ceiling effect', whereby the higher up the social hierarchy one resides, the less relevant weak ties become. Due to the principle of homophily, for the socioeconomically privileged, strong ties will occupy a similar position and should be more willing to provide assistance than weak ties - and there incidentally is little room for upward mobility anyway. Therefore in terms of employment outcomes, the use of weak ties has a much greater capacity to provide a bonus to whichever outcome used (i.e. wages, occupational prestige, quality of employment) for those suffering from a social capital deficit. As Lin (2000) points out, this theory was under-researched at the time of writing - and still is today. This is potentially due to the complexities undertaking such research creates.

Lin *et al* (1981) do test the ceiling effect hypothesis. Using the outcome of Duncan's SEI – a scale of occupational prestige – their models showed a levelling off of the beneficial effects of weak tie usage as the respondents' occupational prestige grew. These results must be treated with caution today though for two linked reasons. First, (and the same can be said for Ericksen and Yansey, 1980; Kramarz and Skans, 2014) the data analysed is situated within what must be thought of as a different historical period. And second, Lin *et al*'s coding of contacts into 'weak' or 'strong' may be problematic. They coded all relatives and neighbours as strong ties. It can be argued that an Aunt that you only see at Christmas is not a strong tie, and that in a global world where a decline of traditional community is often perceived (e.g. Bauman, 2001), neighbours are less likely to be considered strong ties.

Reviewed literature provides strong support as to the efficacy of beneficial social connections in the context of employment outcomes. It appears apparent that these broad benefits are stratified, marked in many cases by characteristics that signify structural inequality in employment outcomes, such as sex (e.g. 'the gender pay gap'; Brynin, 2017) and ethnicity (e.g. 'the ethnicity pay gap'; Longhi and Brynin, 2017). A close correlation of social capital and employment inequality markers further supports the concept of social connections as instrumental within career management. The interaction particularly between weak tie social capital and structural disadvantage is complex and should be treated as central to any theorisation of the importance of weak ties in career management.

2.5 The Digital Revolution of the Social

Contemporary digital communications platforms provide a novel context to test the strength of weak ties hypothesis. The next sections focus on the still relatively recent, and sociologically under-researched online sphere – with a particular emphasis on SNS as potential sites of social capital generation, maintenance and instrumental use.

Although SNS may simply bring to mind mainstream, ubiquitous platforms such as Facebook or Twitter as a lay definition, one could also define SNS as digital platforms that allow for users to interact socially. The latter, broader definition could apply to comments sections on news websites or product review sections on retail websites. Boyd and Ellison (2007) provide a definition that captures the functional aspects of SNS, and is applied to this study. Such sites allow individuals to:

> '(1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with who they share a connection, and (3) view and traverse their list of connections and those made by others within the system' (p. 211).

Boyd and Ellison's definition emphases the greater networking capacity of an SNS platform (such as Facebook, LinkedIn, or Twitter). This distinguishes them from what can be termed 'social media' (platforms such as Snapchat and WhatsApp, comments sections on websites, shared interest forums, etc) through the ability of users to 'articulate and make visible their social networks'. This definition is operationalised for the purpose of clarity, and to separate the more sophisticated networking capabilities of SNS from social media.

Writing in 1999, when SNS were still collectively very much at their fledgling stage, Nan Lin hypothesised that online social networks were about to bring about a seismic shift in the socioeconomic value of social capital:

> 'I suggest that indeed we are witnessing a *revolutionary rise of social capital*, [italics theirs] as represented by cyber-networks. In fact, we are witnessing a new era where social capital will soon supercede [sic] personal capital in significance and effect' (p. 45).

It would be difficult to argue that social capital has indeed superseded human capital (what Lin refers to as 'personal capital'). However around two decades later, the worldwide growth of individuals using SNS indicates such platforms have become entrenched in everyday life for many. As of April 2019, the figure of people worldwide who actively used a social media account was 45% - an increase of 6% from April 2018 (Kemp, 2019; pp. 6-7). Facebook, a SNS, is the most used 'social media' platform within these figures (p.24). In relatively affluent countries where technologies are more affordable and the infrastructure to support online activity is more advanced the figures are higher. For example, the number of active social media users in the US is 79% of the total population (Clement, 2019a), and 67% in the UK (Battisby, 2019).

Rapid and consistent growth of online social networking has led some commentators, such as Lee Rainie and Barry Wellman (2012), to argue that it represents a 'digital revolution' in our social lives. In their book *Networked: The New Social Operating System* Rainie and Wellman portray an optimistic vision for human sociability in the internet age enabled by the relative ease of creating and maintaining social ties through SNS. Their vision contrasts with the concerns of other authors such as Putnam (1996; 2000); who argued that technologies such as television have eroded shared experience and values. Turkle (2011) also views the internet age as a causal factor behind a perceived decline in frequency and quality of human interaction. Rheingold (2002) raised concerns with regards to privacy and power surrounding networked sociability, as well as consequences for human social life.

Rainie and Wellman (2012) coined the term 'networked individualism' as a concept to describe this social revolution. They noted that whilst many of us now negotiate aspects of our daily lives through the medium of the internet, our experiences are far from uniform. Rather, the network plays host to millions of autonomous individuals who are empowered to shape their online experiences and interactions:

> 'They have become increasingly networked as individuals, rather than embedded in groups. In the world of networked individuals, it is the person who is the focus: not the family, not the work unit, not the neighbourhood, and not the social group' (p. 6).

Their Thesis used as its foundation evidence that suggests social capital through weak ties can create powerful opportunities for individuals. Rainie and Wellman's central argument is that the social networking revolution has created a new world of more equal opportunity through the ability to connect, and maintain connections with, those outside of one's immediate social groups. Not bound by traditional spatial or temporal limitations, the individual's social interactions are characterised by autonomy and individualism. This fluidity ensures one is not bound to traditional, more static social groupings and can navigate bridges across structural holes much more readily, depending on need. This concept of social manoeuvrability imagines a world of liberated, savvy, networking citizens:

> ‘A single self that gets reconfigured in different situations as people reach out, connect, and emphasize different aspects of themselves. Our working visual image of this is an amoeba, with both a core nucleus and constantly changing pseudopods’ (p. 126).

Rainie and Wellman’s conceptualisation of a newly fluid and dynamic social world is actually far from new. Zygmunt Bauman (2000), for example, saw the ‘melting’ of ‘solid’ structures into fluid, dynamic entities as the key feature of modernity. However their application of this observation in context of SNS as a positive force for equality of opportunity is powerful when situated within the context of the tangible, investable social form of capital discussed presently.

Rainie and Wellman (2012) do acknowledge that social capital can be negative, as the literature suggests, using examples - drawing upon empirical literature - of happiness spreading through closed networks as easily as obesity (p. 42). Evoking the spirit of the ‘American Dream’ though, they present accessible anecdotal accounts of individuals that they have met (such as ‘the Johnson-Lenzes’; pp. 3-11), who through hard work overcome traditional constraints to cultivate valuable online weak tie connections. In the case of the Johnson-Lenzes this value was realised when one of the couple fell seriously ill, and a range of sparsely-connected actors were reached out to for support. In another example, ‘Linda Evans’ (pp. 256-262) – a recently divorced, stay-at-home mother-of-three – overcame structural constraints to cultivate layered social networks online that helped to ‘rebuild her life’ (p. 262); from obtaining a PhD, to finding family medical solutions, to managing a family holiday. Advice networks providing help on these fronts were cultivated on-and-offline.

Their implication that networked individualism has reignited the American Dream has flaws however. The marriage of network theory and data pertaining to internet usage, with evidence regarding positive direct-or-indirect career outcomes, is uneasy. Empirical coverage of the former two is likely extensive enough to satisfy academic rigour, but too much weight is given to anecdotal examples of a few extraordinary individuals by way of evidence relating to outcomes. The structural constraints resulting in the stratification of social capital possession and outcomes from instrumental actions are apparently swept away by a series of globalising trends – with internet connectivity at the centre. They do acknowledge briefly that the digital revolution may not be as egalitarian as the tone of their book suggests with a nod to ‘scepticism literacy’ – ‘the ability of individuals to evaluate what they encounter online’ (pp. 273 – 274). But, also largely ignore a body of evidence suggesting that structural constraints often replicate themselves within the digital sphere (see Robinson *et al*, 2003 for a good summary).

The American Dream often presents life in the US as meritocratic. A ubiquitous ideal that is represented across popular culture. From in advertising (Marchand, 1985), to sporting events (Tomlinson, 2006), to movies (Rosenberg, 2011). The central tenet of the American Dream; work hard and you, too, can enjoy success, has long since been debunked as a red herring by Robert King Merton (1938); a fantasy that ignores a range of structural constraints dragging on equality of opportunity. As the literature presented in the next section surrounding the 'second-level digital divide' indicates, Rainie and Wellman's (2012) digital revolution could be regarded as a red herring for similar reasons. Although most Americans, and citizens of other wealthier nations have access to the internet (and therefore SNS), not everyone has the necessary means to exploit such platforms and wider internet spaces. Existing offline inequality is often mirrored online (Robinson *et al*, 2003; Hargittai, 2008a; Hargittai and Hsieh, 2013).

2.6 The Second-level Digital Divide

The concept of a 'digital divide' existing between people with and without access to the internet is now well articulated (see Bimber, 2000; Bucy, 2000; Norris, 2001 for examples). Robinson *et al* (2003) provide a summary of the implications of this debate:

> 'Digital divide implies that significant minorities of the population are effectively denied access to a technology that, like other public facilities like libraries and superhighways, is thought to be open to everyone' (p. 2).

Given the perceived advantageousness of being a networked individual, this issue must still be considered valid in the context of much of the world's population still not being 'online'. 58% of people on the planet are classed as internet users (Kemp, 2019). However, in more affluent countries such as the US (84% in 2018; Clement, 2019b), and the UK (90% in 2018; ONS, 2018), a large majority of people use the internet (figures differ depending on methodology used). It is within this context of mass internet use that some commentators such as Robinson *et al*, (2003), Hargittai (2008), and van Deursen and van Dijk (2014) called for a shift in focus in the digital divide debate towards differences amongst the online population.

Empirical evidence from Wei and Hindman's (2011) study showed that education (as an indicator of socioeconomic status) was the only demographic influence that could predict both internet access and informational use. Education in turn was more closely associated with informational use of the internet than with access. These findings support the shift in debate as they show that a population divide is more evident in how the internet is used than overall access. This shift incorporates the central concern of the original digital divide distinction – that access to networked technologies is unequally distributed – but recognises that once access becomes more equally distributed, distribution of uses and outcomes are not uniform. The underlying assumption of the second level digital divide literature considers the internet to have the potential to create equality of opportunity (through human capital-enhancing activity), as Rainie and Wellman (2012) suggest - but significant barriers can prevent such positive outcomes occurring.

A theoretical rationale underpins the notion that 'the term *digital inequality* [italics theirs] better captures the spectrum of differences associated with ICT uses' (Hargittai, 2008a; p. 937). The increasing 'knowledge-gap' hypothesis, first articulated by Tichenor *et al* (1970) indicates that highly educated individuals would benefit more from consumption of information via the media because they have better capacity to absorb it and use it to their advantage. Such a pattern, note Hargittai and Hsieh (2013), widens 'existing inequalities between different population segments' (p. 131). Robinson *et al* (2003) apply the increasing knowledge-gap hypothesis to the internet medium as a whole - encompassing SNS - finding that level of education was the strongest correlating factor with uses considered more likely to help contribute to an individual's human capital. Such uses in that study were related to 'work, education, political and social engagement, as well as … fewer entertainment or avocational uses' (pp. 17-18).

Further research supports the increasing knowledge-gap hypothesis associated with internet use. Hargittai and Hinnant's (2008) findings linked education as well as autonomy, experience and quality of access to online activities likely to enhance human capital. Skill was found to be an important mediating factor. Assessment of skill levels was made based upon level of understanding what is meant by a series of internet-related terms. Further, van Deursen and van Dijk (2014) found that whilst respondents with lower levels of education generally spent more hours per day on the internet, these uses were less beneficial than those of respondents with higher educational attainment in terms of building human capital. This indicated a 'usage-gap' as a consequence of the knowledge-gap between stratified groups. Van Duersen and van Dijk classified information searching, news consumption and personal development activity (such as searching for courses) online as contributing towards human capital. Wei and Hindman (2011) compared respondents' informational use of media to political knowledge. Their findings led them to suggest that the online 'new media' knowledge-gap is more pronounced than the knowledge gap produced through 'old media' such as print newspapers and television. This is possibly because new media requires a greater level of 'active engagement' on the part of the consumer (van Duersen and van Dijk, 2014; p. 509). Education was also found to be the only demographic factor that predicted use of the internet for informational purposes significantly (Wei and Hindman, 2011).

Hargittai (2008b) added another layer of evidence to the relationship between educational background and productive use of online time. In examining how users navigated 'links of influence' – links displayed as outputs of search engines – she reported that critical judgement was strongly associated with a high level of education. Such critical judgement is important, asserts Hargittai, because 'savvy about the medium will assist users in sidestepping potentially misleading and malicious content' (p. 85). Searches performed through engines such as Google, or Bing, generate results based on an interaction of factors pertaining to commercial interests, politics and the input search term(s). These contextual factors can ultimately shape the browsing experience of the internet user and therefore being able to identify content that is biased or misleading should generate more positive outcomes. In her empirical work a sizeable amount of her sample – who are College students and therefore presumably relatively well-educated – were not aware of fundamental aspects of the commercial model of search engines, and therefore that there are underlying agendas which shape the user searching experience. This issue is particularly pertinent in light of 91% of online adults in the U.S. using search engines to find information in 2012 (Purcell *et al*, 2012).

Widening the new digital divide debate from the link between educational attainment and human capital-enhancing activity online, further evidence challenges the optimistic thesis of Wellman and Rainie. Dobransky and Hargittai (2006) identify a 'disability divide' between the disabled and non-disabled online population. One may consider that for many disabled people, the internet and ICT's generally have excellent potential to provide technological solutions to help overcome barriers that are faced in day-to-day life. Certainly, the authors detail evidence of such solutions; for example the proliferation of online social support networks and positive health benefits for disabled internet users (p. 314). Such equalising benefits are negated by a lack of consideration for the disabled at the design phase however. Hardware or software may not be specially configured to allow those with special requirements to use it, including many websites that do not make special provisions for disabilities. Further, 'much assistive technology is reactive in design' (p. 316), meaning that specially designed technology to adapt ICT's are developed after the release of the original, unadapted ICT and by the time the adaptations have been brought to market, the original technology has moved on. Adapted technologies brought to market can sometimes also be prohibitively expensive (p. 317).

Generational effects within internet use was an area of the second-level digital divide forecast by Prensky (2001). The emergence of cohorts of 'digital natives', for whom connected technologies are ubiquitous during formative years and beyond, would facilitate differentiated uses and associated outcomes. The role of age within the second-level digital divide receives less attention from authors prolific in the area such as Eszter Hargittai compared to factors such as education. However the concept of the digital native has received attention in policy circles, particularly in higher education, which has been compared to a moral panic (Bennett *et* al, 2008). Responsive research outputs finding that younger university students do not engage in radically different learning styles to older peers through IT use questions the validity of such attention (e.g. Margaryan *et al*, 2011). Despite this, evidence highlights age as a signpost of 'advanced interaction with the internet', alongside gender and education (Helsper and Enyon, 2010).

Evidence of a new digital divide, based not upon internet access versus no internet access, but on the spectrum of skills existing amongst the proportion of individuals who are online – and its impact upon human capital-enhancing outcomes – is compelling situated within the context of the present study. Although the internet provides undoubtedly opportunities to enhance human capital, the evidence from literature presented thus far suggests that attainment barriers existing in the physical world are mirrored in the virtual, online sphere. Consequently, exploration of such barriers should be factored into any debate or empirical work considering the utility of the internet as a productive tool.

SNS are identified as a key component of Rainie and Wellman's (2012) networked individualism. Such widely used and popular platforms connect the individual with multiple networks whilst being primarily centred around the experience of the user. The next section progresses to present empirical evidence from the growing field of study shining a spotlight on the role of SNS specifically in producing and maintaining social capital.

2.7 SNS and Social Capital

Research focusing on the utility of SNS as a tool to aid social capital development and maintenance is a relatively recent, but established area. Such research typically focuses on levels of social capital - indicating access to social resources for an individual, embedded within networks (e.g. Hargittai, 2008c; Steinfield *et al*, 2008; Donath, 2008; Vitak and Ellison, 2012). Some studies focus on instrumental use of such resources (e.g. Fuels *et* al, 2014; Gee *et al*, 2017).

Haythornthwaite (2002) assessed the effect of 'new media' on social relations. Her work identified preferential conditions for information to proliferate between weak ties online. Haythornthwaite identifies why SNS should be particularly useful for establishing and maintaining relations with connections who are not strong ties, through providing:

> '(the) Means and opportunities for previously unconnected actors to communicate … in particular by laying an infrastructure of latent ties … and providing an opportunity for weak ties to develop and strengthen' (p. 385).

Modern SNS, by including an articulation of user networks and how an individual fits into them (example – seeing who an unconnected user is 'friends' with from your network on Facebook), provides a supporting infrastructure conducive to forming connections with friends of friends, or other forms of latent ties. These ties can then strengthen through a variety of reciprocal actions – such as retweeting, liking a photo, or interaction on comment threads.

A number of papers provide support for the notion that use of SNS platforms promotes greater levels of social capital. Park *et al* (2012) identify a positive association between intensity of smartphone use and intensity of SNS use. Chan's (2015) study shows that online communication via smartphone is related to various indicators of bridging and bonding social capital. Welles and Contractor (2015) also find that time spent using a platform predicts the formation of relationships, in the context of an online gaming world.

Ellison *et al* (2014) measured levels of bridging and bonding capital on Facebook, and found that informational use (making 'mobilisation requests' amongst network) was positively associated with both bridging and bonding social capital. Further, respondents who scored well on the study's measure of bridging social capital particularly valued the ability to interact with friends of friends (latent ties). Steinfield *et al* (2008) found that Facebook was particularly supportive of bridging social capital due to its 'large and heterogenous network' enabling 'lightweight contact' with a broad set of acquaintances. They identified users with low self-esteem as gaining a particular boost to their bridging social capital, as non-face-to-face interactions helped mitigate social anxiety.

Vitak and Ellison (2012) found that participants used Facebook for information-seeking frequently, and that they saw the heterogeneity of networks as a particular strength. A caveat of this research was finding that social anxiety is an inhibiting factor towards accessing embedded social resources through mobilisation requests, because of 'context collapse'. This occurs due to mechanisms designed to proliferate the size of networks (publicisation of content produced by the user, being viewed by unintended audiences), the original context of a post can be rendered invisible, connoting a potentially different meaning.

The above evidence lends support to Rainie and Wellman's (2012) Thesis. Broad support is found for an association between SNS use and greater levels of both bonding and bridging social capital – without coming close to establishing causality. A lack of causal findings perhaps represents the youth of the field of online social capital research through a lack of effective methodological tools. Separation of cause-and-effect is clearly a significant challenge and a lack of publicly available SNS data likely hinders such developments. The research described so far in this section also highlights caveats mediating social capital-related outcomes (such as social anxiety), but makes little reference to second-level digital divide factors articulated within the previous section. Some research does however account for the divide.

Sloan *et al* (2015) identified an age stratification in Twitter use, through analysis of Twitter user metadata (profile information) to investigate factors associated with Twitter use in the UK. The team found that Twitter users are disproportionately young (nearly 60% aged 13-20). Shpiegelman and Gill (2014) find that amongst a sample of disabled Facebook users, few were cultivating or accessing bridging social capital, instead preferring to maintain strong relationships through the platform.

Differential social capital-related outcomes by gender are suggested by the work of Hargittai and Hsieh (2010). They found that women were more likely to perform what the researchers defined as strong-tie related activities such as maintaining friendships in their sample, but fewer weak-tie related activities such as conversing with strangers. Similar findings are reported by Mazman and Usluel (2011). In context of other characteristics, Hargittai (2008c) discovered differential SNS usage by ethnicity, as well as relating to parental levels of education. Hargittai's findings led her to conclude that based on differential usage of SNS, research should not solely focus on differences between 'SNS' or 'non-SNS' users, instead recommending focus on uses and associated outcomes amongst users.

Much research regarding social capital development and maintenance via SNS is not linked explicitly to career management skills through employment outcomes within data, although some research has been undertaken within this area. Matzat and Sadowski (2015) find no support for the efficacy of SNS as a tool to help achieve employment via embedded social resources. Amongst their sample, time spent using SNS did not predict having contact with a hiring employer, whereas operating a blog and using forums were both online activities positively associated with this outcome.

Gee *et al* (2017) generated a sample of 17 million Facebook users by scraping metadata from their profiles across 55 countries. Their research found that weak ties did play a larger role in achieving employment than strong ties, but this was in effect because weak ties are much more numerous. On this basis they conclude that a single strong tie is better than a weak tie as an informal method of achieving employment.

Fuels *et al* (2014), examining the use of social media in the context of employment outcomes amongst unemployed users, finds limited support. Respondents that had positive perceptions of SNS used them more, and engagement with technology also drove usage patterns. Those who used SNS were less insecure about their employment status and less socially excluded. Perhaps most importantly taking into account the second-level digital divide, the Authors found that new skill sets would be required for many of their sample to reap perceived network resource benefits from SNS.

Few studies presented evaluate the efficacy of SNS use within career management taking into account all relevant factors raised within this literature review. Theoretical strands are often tested in isolation of each other. Research can be broadly grouped into three categories. The first contains studies that test SNS efficacy in building and maintaining weak tie relationships (or bridging social capital). These generally find support but often do not account for other relevant factors, and struggle to establish causality. Those with lots of friends or acquaintances may be more likely to use SNS. The second group are studies which consider the second-level digital divide within SNS use. These are not usually located within the context of career management explicitly. The third group locates SNS use within career management, but does not properly consider the second-level digital divide. Some studies (e.g. Fuels *et* al, 2014) are broader in scope and attempt to account for all such factors. This kind of research is relatively rare, and the area requires further contributions.

2.8 Literature Summary

To summarise the theoretical and empirical evidence presented as justification, and context for the present study. The starting point of this literature review was the Scottish Career Management Skills Framework (SDS, 2012). The aspects of CMS under scrutiny are two interrelated competencies in the context of employment markets within mass-connected societies; internet skill and online networking. The ability to use internet services and to be able to critically assess content online is commonly seen as a key competency in the capacity for lifelong learning in European CMS frameworks (Sultana, 2012). Building effective networks of social support to assist with career-based lifelong learning is additionally identified as one of four key competencies in the CMS framework for Scotland (SDS, 2012). Social networking sites are becoming increasingly a ubiquitous part of social lives in countries with widespread internet access (Kemp, 2019). This project investigates use of SNS to manage social capital – and in particular, weak tie social capital – alongside productive uses of the internet generally. This dual strategy is undertaken because SNS are one part of a wider internet sphere and require similar competencies to use productively.

Key to the aforementioned aspects of CMS frameworks are the concepts of human capital and social capital. Respectively, these are the collection of skills that form one's job market value (Becker, 2008) and the aggregate of resources and knowledge embedded within an individual's social ego-network (Lin, 1999). The ubiquity of internet access and popularity of SNS in advanced economies such as the UK and US have led to some commentators hailing the present, connected era as providing greater equality of opportunity for attainment in career management (Rainie and Wellman, 2012). SNS enable individuals to better access and invest in their bridging social capital through their weaker social ties or latent ties (acquaintances or potential social connections). Bridging social capital is strongly linked to career benefits such as receiving information leading directly to a job (direct career benefits) (Granovetter; 1973, 1974), or information that can help improve one's human capital (Vitak and Ellison, 2012) – leading to better employment outcomes (indirect career benefits). The wider internet sphere also promotes equality of opportunity through providing access to a wealth of human capital-enhancing information, such as researching health and financial information online (Hargittai and Hinnant, 2008).

Evidence in support of the primacy of weak ties and bridging social capital over strong ties and bonding social capital within the context of career-benefitting outcomes is relatively mixed. Some studies find distinctive positive effects on outcomes such as wage levels for respondents who utilised bridging social capital to help gain employment, and some others positive effects from the use of bonding social capital. Empirical evidence certainly indicates that levels of social capital and value of associated returns are unevenly distributed. These disparities reflect wider structural inequality.

Contextualised by the widespread availability of internet access in advanced economies the original concept of the 'digital divide' (haves versus have-nots) has been refreshed to represent disparities in online skill levels amongst the 'online' population (Hargittai, 2008a), however. The 'knowledge-gap hypothesis' (Hargittai and Hsieh, 2013) asserts that those who have greater levels of skill or intelligence have a greater capacity to benefit from the opportunities for self-improvement that the internet affords. Further, a body of literature now exists that identifies differentiations of internet usage (for example Dobransky and Hargittai, 2006; Wei and Hindman, 2011; van Deursen and van dijk, 2014) – and therefore outcomes. The disparities are not dissimilar to those identified regarding how social capital operates – broadly representative of structural inequality (Hargittai, 2008a).

An original contribution of the Thesis is to identify stratifications in social capital returns in relation to CMS outcomes, situated within the context of SNS use. In the field of social capital and SNS use, studies investigating CMS-related outcomes are in short supply. Due to the youth of the field, a sociological analysis placing inequality centrally ensures the production of impactful knowledge. Such an investigation – subject to standards of academic rigour – provides a thorough testing of Rainie and Wellman's (2012) influential and egalitarian vision of nations of savvy, connected individuals.

2.8.1 Literature gaps

Based upon evidence presented relevant to the overarching research question of this Thesis (The Role of SNS in CMS), a number of 'literature gaps' can be identified. These missing or understudied elements within the research literature provide opportunities for the current study to address – thereby producing valuable, original academic knowledge. These gaps are summarised thus:

- **Gap A** – The situating of the study of career-oriented online networking and human capital-enhancing activity strategies within the context of the second-level digital divide.
- **Gap B** – An assessment of the influence of weak ties within career management (both direct and indirect career outcomes) in the context of SNS use.
- **Gap C** – A UK-and-Scotland-specific contribution to the literature regarding career-oriented SNS networking and inequalities in online human capital-enhancing activity. The majority of related findings are based upon research carried out in the US.
- **Gap D** – Identification of uneven distribution of career-related positive outcomes from using SNS and wider online space amongst occupational strata and socioeconomic characteristics.
- **Gap E** – Investigation of uneven returns from instrumental use of weak ties within career management, in context of SNS use.

2.8.2 Research Questions

The following research questions have been formulated with the aim of filling the gaps in the literature presented – thereby generating academic value. The research questions also aim to guide the study towards creating further 'impact' in; assessing the usefulness of SNS as a networking tool of the CMS repertoire, exploring the effectiveness of social capital use in relation to career outcomes in the networked age, and identification of effectiveness by characteristics and social strata.

The research questions cluster around two broader themes. A summary of the methods that are employed to address these questions is outlined, with greater methodological detail provided in Chapter 3 (Methodology). Table 2.1 details research question A.

A) Does SNS use benefit career management?
A1) How important is social capital in the contemporary employment market?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?

Table 2.1: Research question A.

The first research question category aims to establish the importance of the internet within career management. Significant weight within this is placed on SNS use as a tool to utilise weak tie social capital. Question **A1** initially tests the effect of social capital use in relation to employment outcomes, as a key theoretical plank (e.g. Granovetter, 1973; Lin, 1999) informing the hypothesised benefits of SNS use (Rainie and Wellman, 2012). Question **A2** follows on from **A1**, in testing the efficacy specifically of weak ties within instrumental use of social contacts. 'The strength of weak ties' (Lin *et al*, 1981; Granovetter, 1983) is again a key plank of the hypothesised career-related benefits of SNS use. Question **A3** broadens the investigation from SNS to wider online space in to explore the impact of internet use within career management in comparison to offline strategies. This also serves as a comparison point when testing efficacy of career management strategies involving the use of social capital – for example comparing job-search techniques in context of employment-related outcomes.

Research Question 2 is of a similar format to Research Question 1, addressing the question of who benefits from the hypothesised bonuses granted to CMS (Rainie and Wellman, 2012) from use of SNS. Focus within this over-arching question is provided through three sub-questions, outlined in Table 2.2.

B) Who embraces the career-enhancing capacity of SNS?
B1) Is there evidence of a second-level digital divide amongst SNS users?
B2) Who uses the internet to enhance human capital?
B3) Is there an uneven distribution of positive, career-outcome effects from weak tie social capital?

Table 2.2: Research question B.

Question **B1** directs research towards identification of whether differentiated uses of SNS and associated outcomes are evident amongst users, in context of career management. Identification of such patterns would indicate influence of the second-level digital divide (Hargittai, 2008a). To more thoroughly investigate the extent that the divide influences accumulation of human capital (e.g. Wei and Hindman, 2011; van Deursen and van Dijk, 2014), Question **B2** addresses productive internet usage patterns and associated outcomes. These patterns are compared to findings from Question **B1** to compare the dynamics of the second-level digital divide amongst SNS users, and internet users. Question **B3** tests for differentiated outcomes from use of weak tie (or bridging) social capital (Moerbeek *et* al, 1995; Torres and Huffman, 2002) in context of SNS use within career management.

Research questions are addressed through quantitative analysis of primary and secondary data. Regression models enable identification of effects at statistically significant levels, whilst controlling for factors which may mediate outcomes. Therefore the chances of identification of 'false positives' – or spurious relationships – is reduced. Many of these models situate analyses within CMS through operationalisation of outcomes reflective of either skill development, job attainment, or job quality. Within such models influence of factors identified within the literature review as contributive to the hypothesised benefits of SNS use to manage social capital are tested for influence on these outcomes. Testing of these key theoretical planks in this way, as well as influences of types of productive SNS use, addresses both the underlying factors behind the hypothesised benefits of SNS use as part of CMS strategy, alongside effects of types of SNS use. This investigative strategy was developed to comprehensively investigate the PhD topic.

Relevant indicators were discovered in publicly-available secondary data. Analysis of these provided a strong base to build the Thesis upon. Coverage of relevant indicators found was however, incomplete. Therefore, bespoke primary data was collected to ensure sufficient scope of analysis. For example, use of social capital in context of career management was found within Understanding Society (University of Essex, 2018) through a variable which indicated whether unemployed respondents actively looking for work had asked personal contacts about vacancies. However, the variables are not complimented by additional data pertaining to the relationship that the respondent has with the personal contact. Therefore, influence of strong and weak ties respectively could not be evaluated. Collection of primary data allowed for such differentiation.

Each analysis chapter (4-8) is based upon datasets used. They are not organised by research questions. This is partially because analysis within each chapter collectively address the majority (or all) of research questions, but mainly because indicators within datasets and sites of analysis provide an opportunity to address the central Thesis question within different contexts. Each chapter provides a guide of how analyses presented within address research questions.

Relevant findings at aggregate (i.e. population) and contextual (granular) levels include advantages of SNS use within career management strategies, efficacy of access to heterogenous networks of weak ties, how skill levels impact productive internet use, and who is likely to have a skill deficit.

Chapter 3: Methodology

3.1 Introduction

It is clear that although SNS may have the potential to be useful tools for career management, inequalities in outcomes associated with social capital and internet use should present formidable obstacles for sections of the online population. The utility of SNS use to access weak tie social capital as a career management strategy (Rainie and Wellman, 2012) is explored in the present work, situated within a UK-and-Scottish context – addressing gaps within academic research literature, and stakeholder interests.

The present chapter details the methodological underpinnings of this study. Section 3.2 situates the epistemological spirit of research undertaken within broader discussions on research philosophy. Section 3.3 details ethical considerations. Processes entailed within the primary research component are described and reflected on in Section 3.4. Section 3.5 addresses secondary data, and Section 3.6 outlines and considers the validity of methods used to analyse data. These sections provide detailed background context for analyses presented in chapters 4-8.

3.2 Impact and structural approach

3.2.1 Research impact

This Thesis is co-funded in a partnership between the Economic and Social Research Council (ESRC) and Skills Development Scotland (SDS). Both organisations encourage 'research impact' from doctoral research projects. The notion of 'impact' is a contentious issue within the social sciences, where even what constitutes impactful research is debated. A fundamental question is whether internal (academically-focused) or external (wider audience-focused) impact should be prioritised. Broadly, internal impact is more likely to create advances within the academic field, but be less accessible and/or applicable to external stakeholders. Conversely, externally impactful work may be easier to implement by external stakeholders and reach wider audiences, but be seen as reductive or superficial within the academic field (Bastow *et al*, 2014).

Situation of this research close to one pole of the internal-external impact spectrum need not be the case. The ESRC, in defining impact on their website, do identify the two types as separate, but caveat this by stating that research can achieve both types of impact (ESRC, 2019), which is the aim of this Thesis. Specific impact aims were discussed in relation to research questions previously in *2.8.2.* A concise summary of these aims are provided here for easy reference:

- Identification of whether productive SNS use grants a boost to career-related outcomes.
- Identification of contextual factors (e.g. skill level) that mitigate potential boosts.

- Identification of personal characteristics associated with contextual factors (e.g. educational attainment as a predictor of skill level).
- Assessment of influence of social capital on career-related outcomes.

3.2.2 Structure and agency

Social scientific research also often highlights another dichotomy, between structure and agency (e.g. Giddens, 1984) which can have implications for research design. In investigating potential structural constraints that reduce the potential for certain groups to utilise SNS productively in career management, in a hypothesised rebuttal of Rainie and Wellman's (2012) work, the research objectives have an orientation towards the analysis of structural influences. Although the arguments advanced by this Thesis do not wish to ignore a role for individual action, the lack of attention towards the role of systemic constraints identified as causal of the second-level digital divide (Hargittai, 2008a) provide a natural focus on structure for the Thesis. The present work seeks to identify population-level patterns that constrain individual action within UK networked society.

3.3 Ethics

The project's research design was monitored according to the University of Stirling ethical research procedures. Forms describing the project plans were submitted for scrutiny to the General University Ethics Panel (see Appendix 2). Approval was given on 19/12/2016 (Appendix 2a).

Ethical issues that required attention during the research process were in large part associated with primary research, which involved storage of personal data. The secondary research component utilised publicly available data (for the purposes of scientific research), for which the majority of ethical concerns were addressed by the original data providers. Overall, the research design in ethical terms can be thought of as low-risk.

Collection of primary data involved two stages which raised different ethical considerations. Stage one was to pilot the survey instrument, which involved some face-to-face contact with pilot respondents as well as online surveys. Stage two – delivery of the final survey instrument to main respondents – was limited to online survey participation with no face-to-face contact.

Survey respondents were; informed of the general subject matter of the surveys, funders of the study, how their data would be stored and potentially used to inform outputs, details of the Researcher's lead supervisor in the event of complaint or enquiry, and assured of anonymity on the front page of the survey. They were also asked to provide their consent to participate on such a basis via providing a tick in a box (see Question 1 in Appendices 1a-1c).

Some face-to-face contact between Researcher and respondents during piloting arose because a paper version of the survey was tested for further education (FE) students, as well as the online version which main respondents completed. Face-to-face piloting was facilitated by a third party organisation, City of Glasgow College Student

Association (https://www.cityofglasgowcollege.ac.uk/studying-city/students-association), who forwarded a recruitment email from the Researcher to all students and provided a venue for the survey to be delivered, allowing for a safe environment.

There was a focus throughout the primary research process to protect anonymity of respondents. Aggregate-level analyses are presented in analysis chapters which do not identify characteristics of individual respondents. All main survey respondents were asked to provide an email address in the event that they were randomly drawn as a voucher winner (as an incentive to participate). Once prize draws were complete, these addresses were removed from derived survey datasets. These unique identifiers are held in a secure user account with the survey platform used, Online Surveys, (https://www.onlinesurveys.ac.uk/). This ensures that respondents are still 'findable' but remains consistent with the University of Stirling Fair Data Guiding Principles (N.D.).

This study adheres to ESRC guidelines on data storage and deletion (ESRC, 2018). All survey data, once downloaded from the Online Surveys account, is stored on a password protected computer which is accessible only to the Researcher. Data is treated as if it were personal and sensitive.

3.4 Primary data

A primary data collection strategy was chosen for two reasons. First, secondary data containing combinations of indicators pertaining to the key elements of this study was relatively rare. Second, it was felt that a focus on case study populations at important career phases would provide compelling sites for analysis, and a primary survey offers a flexible way of obtaining suitable data from relevant case studies.

In practice three case study populations were defined in terms of life events and stages which would generally be associated with certain age groups and circumstances. The case study populations are FE students; mothers with young children; and people recently made redundant from their jobs. FE students would generally be considered young people who have recently left school and mothers of young children generally older than FE students but not middle-aged. SDS, who facilitated access to the redundancy population, advised that the population's general profile was middle-aged. In consequence, none of the case study samples were sought to be representative of the whole working-age population, but to focus instead on narrower circumstances. The relative merits of choosing each case study population are discussed in further detail individually in relevant sections in Chapters 6-8.

3.4.1 Survey software

All surveys delivered to main and pilot respondents were designed and distributed via Online Surveys. Paper surveys given to some pilot respondents were print-outs of the online version. These surveys were all produced by the same user account, which only the Researcher has access to. Once a survey had been designed and piloted, it was then made 'live' and a link shared with target audiences. The look and feel of the survey design is accordingly influenced by the online survey platform. Appendices 1a-1c show copies of the relevant surveys used. Once a survey period has finished, data was exported by downloading into a file format associated with Microsoft Excel. After download, the data was subject to statistical analysis that was undertaken using Stata (StataCorp 2017). Syntax files written for purposes of data management, manipulation and analysis are available to download from an online public repository, organised by the data set they are associated with (https://github.com/kaneneedham/PhD-Utility-of-SNS-within-career-management).

3.4.2 Further education student survey

During the literature review phase, it was found that many studies used undergraduate student samples. FE students were therefore chosen as an early-career phase case study to add a novel contribution to the literature. A significant proportion of FE students in the UK are 16-19 years old, for example (gov.uk, 2019). A criteria that respondents were within 6 months of completion of their course was used (i.e. 6 months until finish, or 6 months since finishing) was applied, to ensure that all respondents were approaching, or had recently made, an important career choice at the time of data collection. Data collected regarding research that respondents had done about jobs or further courses therefore comes from a sample that is presumed to be actively engaged in career management processes.

3.4.2.1 Piloting

Piloting the FE student survey was carried out in two modes – online and offline. A paper survey was created in anticipation of seeking an offline sample to eradicate bias which would occur from sending the survey out via the internet only. This plan was later abandoned when it was decided to focus on populations that use the internet in accordance with the focus of the second-level digital divide (Hargittai, 2008a).

Content of paper and offline surveys were identical. Minor divergences related to formatting. Piloting of both survey modes was carried out in the same setting at the same time. Pilot respondents were recruited remotely, and upon arrival at the venue were randomly assigned to complete either the paper or online survey. All pilot respondents (n=20) were then briefly interviewed in focus groups of 3-4 by the Researcher to elicit general and specific feedback on their experiences. These interviews were informal, and not recorded. The Researcher made notes for later reference. Recruitment of pilot respondents was facilitated by the City of Glasgow College Student Association (https://www.cityofglasgowcollege.ac.uk/studying-city/students-association). An advert was forwarded by Student Association staff to all students, inviting participation on a pre-determined date at a venue arranged by the Student Association.

Pilot respondents were incentivised for their participation with a £3 cash payment from the Researcher's ESRC budget. Several points of feedback were incorporated into the final survey including simplification of a question on urban density, simplification of a question regarding highest educational attainment, and a restructuring of questions asking respondents to classify their personal ties to reflect difficulty they had in coding ties themselves into ‘weak’ or ‘strong’. Some respondents thought that the survey was too complex, and others thought it was simple. No consensus was reached on this issue. The conclusion drawn from this final point was that survey respondents are not a homogenous bloc. Characteristics such as intelligence or interest in the subject matter likely influence engagement levels and depth of understanding.

3.4.2.2 Data collection

To provide access to respondents who were within 6 months of finishing, or 6 months of having finished a FE course at a Scottish college, institutions were contacted individually and asked to forward an email to their students which explained what the survey was about and invited participation. A link to the Online Surveys host was included. An incentive to participate was advertised – a prize draw to win 1 of 8 £20 vouchers to spend with a large online retailer.

All 27 Scottish FE colleges were contacted (for a list, see Colleges Scotland, 2017; p.21) via telephone and email. Telephone contact sought to identify a gatekeeper within the organisation with the ability to forward the survey email on to large numbers of students. Voice contact also allowed for conversation, where the Researcher could explain the potential value of participation for the FE sector. In total 19 institutions agreed to forward the survey email to their students. Gatekeeper dissemination patterns were far from uniform. All students at some colleges received the emails, whilst other gatekeepers advertised the survey via other channels of less reach. This (and variation in the size of colleges) was reflected in the institutional distribution of respondents (see Chapter 6). The data collection period ran from April 2016 until June 2016.

Overall, the recruitment strategy involved with this survey seemed relatively successful. It is not possible to ascertain the potential sample size given uncertainties surrounding gatekeeper methods of distribution, and actual student numbers within the specified parameters. The total number of 357 responses to the survey was large compared to responses to the mothers and redundancy surveys. Sponsorship and promotion from an umbrella group for the Scottish FE sector should have produced a greater frequency of responses. This was sought from the College Development Network (https://www.cdn.ac.uk/) via Researcher contacts at SDS and direct contact attempts, but a concrete and positive response did not materialise.

3.4.2.3 Key dependent variable

The key dependent variable employed in analyses in Chapter 6 is derived from a question asking respondents how positive they felt with regards to where their career would be in one year’s time (Appendix 1a; Q4). Built into the design of all primary surveys is at least one indicator measuring career outcomes of respondents, so tests measuring the success of SNS use as part of a career management strategy could be undertaken. Defining an outcomes indicator for the FE sample was not straightforward, given many respondents were unlikely to have established careers. More conventional indicators of career success such as wage levels or occupational ranking scales were deemed invalid. A measure of respondents' positivity regarding their future careers was reasoned a good compromise measure given the context. The distribution of the original variable, and the version derived for analysis, is detailed in Table 3.1.

Original career positivity % (freq.)				
1. Very positive	2. Positive	3. Neither positive nor negative	4. Negative	5. Very negative
23.6 % (82)	**47.3%** (164)	**22.5%** (78)	**4.9%** (17)	**1.7%** (6)
Total: 100% (347)				
Derived career positivity % (freq.)				
0. Not very positive		1. Very positive		
76.37% (265)		**23.63%** (82)		

Table 3.1: Distributions of key dependent variable employed in Chapter 6 analyses – career positivity. Original variable coding and derived coding for analysis.

Responses within the original variable are skewed towards positivity. It was not anticipated that only a fraction of FE students would feel negatively about their future career when the question was designed. Because of this skew the variable required restructuring for analysis into a nominal variable: the difference between respondents being very positive and other gradations of positivity is explored in analyses as a result.

3.4.3 Mothers of young children survey

The survey of mothers of young children was not originally intended to be single gender. The survey was designed and disseminated for parents of young children to complete. However, when the survey closed, 155 of 163 (95%) respondents were female. For consistency, male respondents were removed from all analyses. Further, it is apparent that a gendered selection bias was operating within respondent recruitment, and therefore the male respondents are unlikely representative of the case study population.

The sampling frame was chosen because it was judged likely to capture responses from a sample of adults who may be experiencing, or had experienced relatively recently, disruption in their working lives due to parenthood - and consequently would be a compelling site for analysis of career management strategies. Disruption could occur for parents of young children in a range of guises. Parents may leave and re-enter the workforce, or change working patterns or jobs in response to childcare demands, raising additional challenges within career management. The average age of motherhood in Scotland, 30 years (NRS, 2016), suggested that the population captured would be at a different life-and-career-stage than FE students. The sampling parameter set was parents with a child of primary school age (generally 5-12 years; European Commission, 2019). This was set in order to capture responses from parents who perhaps did not need to care for their children full-time any more if they had left the workforce (lower limit) - and therefore were re-engaging with the employment market – and those who had had a child relatively recently (upper limit).

3.4.3.1 Piloting

Following comprehensive piloting of the FE student survey, less intensive piloting of the mothers' survey was required because it drew many elements from the FE survey. Some structural and semantic changes were made, but a large portion remained the same. Piloting of this survey was carried out online. Pilot respondents (n=8) were recruited through their association with a parenting/family charity, Home Start Stirling (https://www.homestartstirling.org.uk/). Home start Stirling agreed to put a small advert in an online newsletter send to subscribers, who subsequently contacted the researcher expressing interest in participation. Pilot respondents were given a link to the survey and following completion, logged survey feedback via a telephone call with the researcher. Pilot respondents received £5 remuneration from the Researcher's ESRC budget.

3.4.3.2 Data Collection

Main sample recruitment followed the successful means used to attract pilot respondents. Parenting/family charities were systematically identified using the Scottish charity regulator's (OSCR) website (https://www.oscr.org.uk/) via a search function. Search was performed via the keyword 'parent' and setting an income parameter so that charities with annual incomes of less than £100,000 did not appear in results. This was to remove smaller charities with low stakeholder numbers. These charities were then contacted by telephone or email and asked to share an advert with subscribers. Emailing the advert direct to subscribers, or placed within an email newsletter was the preferred option of the Researcher. It was assumed such a method would have the greatest reach, and was a tactic successful in dissemination of the FE students survey. Due to the relative ease of posting a shortened version of the advert via social media, many gatekeeper charities stated they would prefer this method, however. Consequently, the advert was shared via multiple channels.

This survey period ran between December 2016 – April 2017. By April 2017, the survey had received 413 responses and was closed. Upon further investigation of the data, a significant issue with fake responses generated by botnets was discovered (see '3.4.3.3 Botnet attack'). When fake responses were removed, genuine survey responses totalled 137. A subsequent effort was made in June 2017 to attract additional respondents by contacting new charities with a new survey link (a copy of the original, changed URL). This was of limited success. 26 respondents completed the second survey, bringing total responses to 163. All respondents who left an email address within their survey response were entered into a random prize draw to win 1 of 10 £20 online retailer vouchers, funded via the Researcher's ESRC budget. As the removal of bot responses left a small sample of human respondents, the sampling strategy for this survey can be considered to be flawed. A large number of charities were contacted, but the outcome suggests that the time invested in identifying and contacting charities might have been spent better pursuing an alternative strategy. Contacts of the Researcher at SDS were also used to try to attract further sponsorship of the survey (for example from large charities), but these were not successful.

3.4.3.3 Botnet attack

The following sub-section details two 'botnet' attacks which compromised the survey of mothers, and provides a brief reflection on wider consequences for academic research.

A botnet (often simply referred to as a 'bot') is a computer program which can fulfil a range of function autonomously, at the programmer's behest. They are a ubiquitous part of the internet landscape, performing functions ranging from moderating comments in chat rooms (Ciano and Ghimire, 2018), to mining the cyptocurrency Bitcoin (Panda Security, 2017).

It was initially discovered that the survey had been compromised by botnets when the Researcher did the survey respondent prize draw. Respondents that were randomly chosen as winners were emailed, asking for them to reply to confirm that their email address was valid, before the e-voucher was sent to them. All replied, although more than half of the responses came within minutes of each other, and contained a similar style of broken English. These 'suspect responses' had strange names assigned to the email address. Instead of, for example, 'Kane Needham', examples are 'green dave', 'Rfnd Fndkf', and 'Grpp Fko'. Further, the email addresses all conformed to a similar pattern of a 7-or-8-letter English word, followed by two letters, and the suffix '@gmail.com'.

Investigation of the data confirmed the compromise. Descriptive analysis showed implausible distributions from these responses on several variables. For instance, the modal response category to a question on how many children the respondent had was '5 or more'. More of these respondents also said that they came from Wales and Northern Ireland than Scotland, despite the survey being distributed solely via Scotland-based charities. Analysis of data conducted by an interested academic working at the University of Stirling (Prof. Alasdair Rutherford) was systematically able to separate 'bot' and human responses, based upon time stamps and response patterns. Two separate bot attacks occurred. Professor Rutherford provided evidence via graphs showing distinct response patterns. These can be found in Appendix 3. Based upon the syntax file, the bot responses were removed from the dataset.

On reflection for wider academic survey research, this episode suggests that vigilance should be exercised when online surveys are released into the public domain – particularly when a monetary (or as in this case, voucher) incentive is attached. It is suspected that the bot attacks targeted a link to the survey which may have been found via the relatively open domain of Twitter, where the survey was promoted by some organisations. Other channels, such as Facebook, can be less accessible to non-stakeholders (e.g. a private group operated by the parenting charity). It is also possible that the survey link was found because the bot owner(s) subscribed to a mailing list belonging to a participating charity, which is the other known dissemination channel. All of these dissemination means are routinely deployed in low-cost online survey projects, so all might raise risks of similar outcomes.

3.4.3.4 Key dependent variable

The format of the key dependent variable measured within this sample was kept the same as in the case of FE students, with subtle modifications. Instead of being asked to rate on a scale of 1-5 how positive respondents felt about where their career would be in one year's time, mothers were asked how optimistic they felt about their career at the moment (Appendix 1b; Q32). The semantic change (positive to optimistic) captures the same spirit. The more concrete change (one year's time to present) reflects the lack of a contextual cue to warrant asking about the future (many FE respondents were still studying a course, and therefore presumed not in, or pursuing, career-oriented employment).

More conventional measures representative of outcomes stemming from career management strategy (e.g. wages, attainment of a job) were again deemed inappropriate because a proportion of respondents were assumed to be temporarily out of employment, or in reduced employment, because of childcare duties. The distribution of the original variable, and the version derived for analysis, is detailed in Table 3.2.

Original career optimism % (freq.)				
Very optimistic	**Optimistic**	**Reasonably optimistic**	**Not very optimistic**	**Not at all optimistic**
11.2% (17)	**28.29%** (43)	**29.61%** (45)	**23.68%** (36)	**5.92%** (9)
Total: 100% (150)				
Derived career optimism % (freq.)				
Not very optimistic			**Very optimistic**	
59.21% (90)			**39.47%** (60)	

Table 3.2: Distributions of key dependent variable employed in Chapter 7 analyses – career optimism. Original variable coding and derived coding for analysis. N = 150.

Although responses are fairly evenly distributed amongst categories within the original variable, it was dichotomised because of low absolute response numbers to the survey. A further reason was to maintain consistency with FE student sample analyses.

3.4.4 Redundancy sample survey

The final survey targeted people who had been made redundant from their job in the last three years at the time of data collection. A sampling frame was available of respondents who had contacted SDS about receiving some form of redundancy support. This implied respondents were either active jobseekers, or had recently been. Further, SDS contacts had informed the researcher that redundancy support clients tend to be older jobseekers, who often find it more difficult to get work than younger jobseekers (SDS, 2017). Older people are also identified in the literature review as theoretically less likely to be able to utilise digital technologies (Prensky, 2001) productively. Given these factors, people who had recently been made redundant and sought SDS support comprise a compelling population for a case study analysis of how useful SNS are in the jobseeking process.

3.4.4.1 Piloting

The survey designed for the redundancy sample was an edited version of the mothers' survey, which in turn grew out of the FE students' survey. The level of development (including two pilot studies) that had already gone into much of the survey instrument meant that only limited additional piloting was needed. Two pilot respondents were recruited via informal channels, who were contacts of colleagues of the Researcher. These respondents had been made redundant from their jobs 1-2 years previously. The same process was used as when piloting the mothers' survey – pilot respondents filled in the survey online, and then engaged in a short telephone conversation with the Researcher regarding their experience. The pilot respondents were each reimbursed £5 from the Researcher's ESRC budget.

3.4.4.2 Data collection

SDS acted as gatekeeper in facilitating access to respondents who had approached them for redundancy support in the previous two years. Redundancy support exists through SDS's Partnership Action for Continuing Employment (PACE) programme (SDS, N.D.). SDS forwarded an email advert for the survey to a potential sample of around 3,000 individuals. The final number of responses received was 156. These responses were received after the advert had been sent to the potential respondents three times. Respondents were given reimbursement for their time via entry into a prize draw to win 1 of 10 internet retailer vouchers, funded through the Researcher's ESRC research and training budget.

It was hoped that more potential respondents would fill in the survey, but at a time when voluntary surveys generally attain low response rates, and web surveys have been found to yield 11% lower response rates than other modes (Manfreda *et al*, 2008), a response rate of around 5% is not implausible.

3.4.4.3 Key dependent variable

The key dependent variable operationalised in analysis of this data represents job attainment. It is a binary indicator of whether respondents had got another job, following being made redundant within the last three years. It is employed primarily in analyses that seek to measure influences of instrumental social capital use via SNS on the likelihood of respondents gaining re-employment. Other analyses also compare instrumental social capital use via channels other than SNS, in tests designed to determine whether SNS use grants a bonus to career management within use of social capital in job seeking. These analyses control for length of time since the respondent was made redundant, as this was found to have a significant effect in predicting re-employment. Table 3.3 details distribution within this variable, which is produced from survey question 23 (Appendix 1c). Most respondents (65%) had gained re-employment. A sizeable portion (35%) had not. On the basis that respondents are assumed to be actively seeking work, based upon their engagement with SDS, the over-arching aim of the chapter is to examine whether key theoretical planks behind hypothesised SNS utility – as well as SNS use itself – appear to influence early exit from unemployment.

Is respondent now employed?	
‘0’ = No	‘1’ = Yes
55 (35.36%)	**101** (64.74%)

Table 3.3: Key dependent variable operationalised in analyses presented in Chapter 8. Measurement of whether respondent has gained employment since being made redundant. N = 156.

Analyses testing influence of SNS use on exiting unemployment via operationalisation of this indicator as dependent variable should consider that other responses to being made redundant from a job exist that can be termed ‘productive’ or ‘beneficial’. Whilst getting a job is likely the main desired response – evidenced through the majority of those surveyed having gained re-employment – some may choose, for example, to study a degree. Such respondents would be classified in analyses as still being unemployed if they did not participate in paid employment alongside study.

3.4.5 Primary data discussion

Primary data collection provided three data sets of case studies that are compelling settings for analyses of the use of SNS in career management.

These data sets should provide a unique opportunity to address research questions, and provide additional insight to complement evidence from secondary sources of data. Barriers occurred in the process of collecting these data that mitigated this added value somewhat. The issue of the mothers’ survey being compromised by botnet(s) has been detailed; as the botnet responses were readily identified there was not a direct challenge to validity, but the response patterns might have led to lower sample size than intended. For both samples of mothers and people who had experienced redundancy, smaller samples of respondents than hoped for were obtained. Subsequent analysis show that the small number of cases probably did reduce the sample power to a consequential degree – for instance, many analytical results failed to reject the null hypothesis when previous studies had found different results.

The lower response numbers than hoped did not necessarily reflect lack of effort in the recruitment or planning processes. Surveys went through several draft iterations before being piloted thoroughly. A large amount of the Researcher's time was spent sending emails and encouraging dissemination by staff in gatekeeper roles via telephone. The Researcher also spent a large chunk of the ESRC research and training budget associated with the project on incentives for respondents to take part. Perhaps it is the case that in the landscape of 'knowing capitalism' (Savage and Burrows, 2007), academic research using the method of an online survey – a very popular market research method – struggles to gain the attention of internet users. Anecdotally, but very relevant to this project, a similar PhD which won funding from the same sponsors used survey data for which collection was contracted out to a private company. A larger number of responses were gained and, as is understood, funding additional to the level that this project had was not attracted (Mowbray, 2017). A wider methodological recommendation stemming from the present project would be that primary survey research with a small budget should consider a careful cost-benefit analysis regarding strategies for promoting the survey instrument.

3.5 Secondary data

Three secondary data sets that contain relevant data were also exploited. Understanding Society (University of Essex, 2017), the Oxford Internet Surveys (Dutton and Blank, 2013), and the ONS Opinions and Lifestyle Survey: Internet Access Module (ONS, 2014). Understanding Society and the Oxford Internet Surveys are the basis of analysis chapters 4 and 5. Initial analyses of the ONS Opinions and Lifestyle Survey were not continued. The following section provides relevant methodological details pertaining to these data.

3.5.1 Understanding Society

3.5.1.1 Data collection and survey structure

Understanding Society is a longitudinal household panel survey, for which 8 waves are currently available for public download (as of February 2019). Data was downloaded from the UK Data Service (https://www.ukdataservice.ac.uk/). Survey data is collected via face-to-face interviews or online self-completion surveys individually from all people within a recruited household (around 40,000 households). Many questions are asked each year (or wave), which are supplemented by rotating question modules. Many respondents recruited in wave 1 are still participating in wave 8. Respondents drop out of the survey for a range of reasons, including refusal to participate and moving to an unknown area. Additional households also become created when original households split (see NatCen, 2012 (Wave 1); Kantar Public, 2017 (Wave 8) for further details). Therefore, longitudinal analysis is possible with Understanding Society data, although this excludes parts of the sampling universe.

Respondent coverage is for the whole of the UK, although the user guide recommends that survey weights are applied to analyses if the analyst wishes to generalise their results, in order to equalise disparities within the sample relating to over-or-under-represented groups (for further details see University of Essex, 2018b; pp. 65-70). These weights are supplied within data files, and are applied to all multivariate analyses presented in Chapter 5.

Results presented in Chapter 5 are generated from analysis of mainstage individual response data (with some linked household-level data) in waves 4-6. Wave 4 data was collected between 2012-14, wave 5 2013-15, and wave 6 covered 2014-16. Respondents who began participation in the survey's precursor, the British Household Panel Survey, are interviewed in year 1, and those recruited solely for Understanding Society in year 2 for each wave (for more details and wave production timeline, see University of Essex 2018b; pp. 14-16).

5.1.2 Scope of data and scope of interest

Understanding Society data is large in scope. Respondents are asked questions relating to a range of social, economic and behavioural factors. Pertaining to the remit of this Thesis, a small number of variables were found covering employment outcomes, methods of job-searches, and SNS use to be operationalised as key independent and dependent variables. These variables are not all part of core question modules. Their status as part of rotating modules limited the amount of relevant data at wave-level, and removed longitudinal analysis options. A large sample size and strong coverage of demographic details allows for generalisable multivariate analyses that control for many individual differences when survey weights are applied. A subsample of jobseekers was analysed, providing a relatively large universe whose progress was tracked over time, with a focus on job-search methods and SNS use in influencing employment outcomes.

Analyses presented track respondents who were looking for work ('in the last four weeks' at the time surveyed) in waves 4 and/or 5, and focus on employment outcomes (e.g. wages, job satisfaction, employment status) in wave 6. Respondents were tracked via unique identifier numbers.

5.1.3 Key dependent variables

Analyses of these data operationalised a range of dependent variables. This is a consequence of the rich amount of variables available in Understanding Society data that measure quality of employment. Information regarding dependent variable structure is therefore detailed and reflected upon within Chapter 5.

3.5.2 Oxford Internet Surveys (OxIS) 2013

3.5.2.1 Data collection, data structure

The Oxford Internet Surveys (Dutton and Blank, 2013) were an ongoing series of surveys collecting data on respondents' attitudes towards, and uses of, the internet. Between 2003 and 2013 data was collected every two years, and released two years after collection to academic researchers and government users, as well as other customers for a fee. The 2013 data set analysed within this project was the last, as the survey was discontinued. Data is collected via face-to-face interviews in respondents' homes. The 2013 data set is comprised of responses from 2,053 people who fit into three categories of internet user: current user, former user, and non-user (never used the internet). Respondents are sampled randomly using a multi-stage process that is representative of the British population – therefore England, Scotland and Wales, rather than the whole UK (for more information see OxII, 2019). Survey weights are provided within the data file and applied to all multivariate analyses presented in Chapter 4. Data was obtained upon request from the survey authors via email.

3.5.2.2 Scope of data and scope of interest

With regards to internet use in Britain, there is not currently available a survey data set of similar scope (OxII, 2019). The data contains multiple indicators of 'productive' (as defined within career management literature) internet use, 'avocational' (as defined presently) internet use, SNS use, and attitudes towards the internet as an informational medium. Some indicators relating to employment are also present. Therefore, the data is ideally suited as a site of analyses addressing the research questions. Compared to Understanding society, OxIS has better coverage of relevant indicators that are operationalised as dependent and independent variables (internet uses, employment outcomes, etc), but has inferior coverage of socio-economic and demographic indicators that would typically be employed as controls within multivariate analysis. When the sample universe is aligned with project aims – non-and-former internet users are excluded – sample size is reduced to 1,430, which may affect statistical significance of multivariate regression coefficients, as is suspected to be the case with primary data sets.

3.5.2.3 Key dependent variable

Multivariate analyses presented in Chapter 4 are, for the most part, logistic regression models predicting whether internet user respondents have found a job online (Table 3.4). This wording is taken to measure whether the respondent has ever gained employment in a job on the basis of information that they found online.

Has respondent ever found a job through the internet?	
0 - No	1 - Yes
1,106 (78%)	**321** (22%)

Table 3.4: Distribution of key dependent variable operationalised in Chapter 4 analyses. Binary indicator depicting whether respondents have attained a job which they were alerted to by an online advert. Sample universe = current internet users. N = 1,427.

Analyses (see Chapter 4) employed indicators that are related to social capital (e.g. use of SNS) and human capital (e.g. checking facts online), as independent variables mediated by demographic controls. These analyses are conducted in order to test whether use of the internet in productive career management contexts significantly predicts a successful employment outcome. Further analyses exploring the second-level digital divide with regards SNS use and general internet use are linked to test for the existence of a subset of productive internet users who experience preferential outcomes.

3.5.3 ONS Opinions and Lifestyle Survey: Internet access module

The Internet Access Module is a non-core question module covering internet uses within the ONS Opinions and Lifestyle Survey (ONS, 2014). Months covered by the Internet Access Module are January, February and April of each year (core question modules cover 8 months of the year). The 2014 data set was considered as a site for analyses contributive to this project because of a relative wealth of internet use/behavioural indicators. Initial analyses were ran to provide familiarisation with the data. Upon reflection, it was decided that this data set was too similar to OxIS 2013 to provide a meaningful addition to the project. OxIS was chosen over the internet access module because it contained a greater range of internet-related indicators.

3.6 Data analysis

The following section provides a brief overview of other methodological aspects of the project. These cover reflection on general strategies used when coding variables, and on analytical methods employed.

3.6.1 Variable coding strategies

Decisions over how best to operationalise variables were made frequently during the analytical process (and in the case of primary research, in design of survey instruments). Due to limitations of space in analysis chapters, it is not possible to provide detail pertaining to all decisions. This sub-section is intended to provide an indication of the strategies generally pursued, in order to show that decisions relating to variable operationalisation are not taken lightly.

3.6.1.1 In survey design

Survey design balanced a desire to collect rich, detailed data against that to avoid overburdening respondents. The burden on respondents is particularly important when collecting data online, as the respondent is unable to ask for clarification. Fine tuning of this balance was a major factor behind each survey going through several draft iterations and piloting. During survey design effort was also made to clearly imagine how the data would be used in analysis. An example of both considerations is evident in the formatting of questions regarding activities conducted online. Here, a tick-box grid format allowed for the collection of very detailed data pertaining to what respondents used the internet for, which was relevant to the research literature. Multiple tick-boxes can be addressed quickly when arranged in this way, reducing demands on the respondent. Analytical options could also be kept relatively open with this format. Respondents could rate the usefulness of an online source of job information on a Likert scale, with a sixth box to indicate that they had not used the method (e.g. Appendix 1c, Question 35). This example leaves the possibility of creating a binary variable indicating whether the respondent had used the source, as well as an ordinal rating of usefulness amongst those who had used it.

When collecting data relating to respondent uses of SNS, respondents were given a definition consistent with that defined within the literature review (2.5; p.16), so platforms of interest such as Facebook and LinkedIn were not confused with social media, such as WhatsApp or a chat room. Subsequently, indicators relating to SNS use within primary data are likely more reliable in relation to the aims of this project than in, for example, Understanding Society (University of Essex, 2017), which asks respondents if they 'belong to a social website'.

3.6.1.2 General strategies in major control variables

Across primary and secondary data, decisions of operationalisation were required for variables that were employed as controls in multivariate analyses. Demands for granularity (retaining level of detail in variables) and functionality in models (a desire for a succinct level of detail with many cases in all relevant categories) were often in conflict. In many such cases, control variables were operationalised in more than one way and tested in models. Through this process the functionality demand prevailed most frequently, influenced by the small sample size. For example, ethnicity was identified in the research literature as a structural marker of inequality in both employment outcomes and in the second-level digital divide. Reduction of an ethnicity variable to its simplest operational form – a binary indicating ethnic majority vs ethnic minority – is a relatively blunt instrument to capture ethnic differentials with, as ethnic minorities are not a homogenous group (Williams, 1996). However sample sizes in primary data and when using OxIS were too small to represent more detailed granularity.

3.6.2 Methods of analysis

Analyses presented in Chapters 4-8 generally follow a similar trajectory, and can therefore be described and reflected on as a whole. The similar approaches reflect the similar formats of data used. The majority of dependent variables are categorical data which was most sensibly operationalised in binary format and analysed by using logistic regression. The following section describes the general format of analyses in order that they usually follow in analysis chapters.

3.6.2.1 Univariate

All variables used in analyses were examined in isolation to determine variable structure, and other important characteristics such as missing data. Demographic variables most commonly operationalised as control variables in multivariate analysis are reported to provide an assessment of sample characteristics and representativeness, which is particularly important in the case of unweighted primary data.

3.6.2.2 Bivariate

Bivariate analysis is routinely carried out as a precursor of multivariate analysis. Detailed results are often not reported in results chapters. Hypothesised relationships between dependent and independent variables as identified by the research literature or warranted by the research questions are tested by using techniques appropriate for the form of inputted variables. Association statistics generated via tests such as Goodman and Krushman's gamma or Cramer's V are checked for statistical significance via a chi-square test. As is common within the social sciences, chi-square figures below 0.05 were interpreted as significant, and therefore a rejection of the null hypothesis. Because of relatively low case numbers in most analyses, figures above this threshold but below 0.1 were considered as suggestive of a significant relationship (Bryman, 2004).

3.6.2.3 Regression

Logistic regression is a very popular method of multivariate analysis in the social sciences (Gayle and Lambert, 2009). This is because dependent variables are often categorical in structure. Logistic regression can test for a predictive effect of an independent variable on the probability of the outcome being in a particular category, whilst controlling for other factors. Other control factors are used to reduce the chance of identification of spurious relationships between independent and dependent variables (Bryman, 2004). Coefficients denoting effect size estimates produced in the analyses are subject to chi-square tests under the same logic outlined in *3.6.2.2*. Interaction effects are explored within models in order to determine differential effects resulting from combinations of independent or control variables (Jacard, 2003).

3.6.2.4 Factor analysis

Factor analysis is employed to identify a latent variable (or factor) that links groups of variables. It is a test conducted on a series of variables that identifies a variable not present in the data which is revealed by combinations of other variables (Bryman, 2004). If variable combinations are found to load on to a common factor, the latent variable may be operationalised as a singular indicator of what the combinations represent.

In present context, an example would be running a factor analysis on a series of indicators measuring behaviours online. If the factor analysis identifies the existence of a latent variable linking behaviours identified as productive use of the internet, it becomes a singular indicator that can be operationalised in one, for example, regression analysis instead of running a series of regressions for each non-latent indicator. Specific uses described in this Thesis include discussion of use of factor analysis to check overlap of measures on use of SNS in Chapter 4, and in Chapter 6 it is used to determine whether different productive uses of the internet are measurements of a single concept (productive use).

3.7 Sampling and analytic strategy limitations

The overall sampling and analytic strategy pursued within this thesis – use of primary and secondary datasets, analysed using quantitative techniques, with focus on case study populations of particular policy relevance – has been justified in relation to the research questions. However, it should be acknowledged that no one sampling or analytic choice is objectively the best way to approach solving a research problem. This section serves to reflect on how these methodological choices – however sensible – have limitations that caveat the utility of findings.

3.7.1 Sampling

Primary data was collected largely due to the value it was seen to add to the study. Existing and accessible secondary data sources, while very useful, did not contain enough of a range of indicators pertaining to, for example, respondent network composition, to provide satisfactory coverage in relation to research questions. Owing to a lack of resources, it was deemed unlikely that larger primary samples that broadly represented the general population would be possible to collect. Therefore, a sensible primary strategy was to collect data from case study populations of particular interest.

A limitation of this strategy is that areas of value added through collection of primary data cannot be generalised to broad populations. Findings pertaining to, for example, influence of using weak ties through SNS when searching for jobs on job attainment for further education students cannot be confidently generalised to wider populations. Although the samples have particular contextual utility (policy makers are likely to view those made redundant recently as more urgent targets for intervention than someone comfortably employed), this utility inevitably does not automatically extend to wider scenarios.

This limitation carries over into sample selection from secondary data sources, albeit to a lesser extent. Theoretically, secondary social surveys enable the researcher to interrogate data to produce findings which apply to the general population (UK in this case). However, when producing a detailed analytical strategy, it became apparent that sub-samples within the two data sources upon which analysis chapters are based (Understanding Society and Oxford Internet Surveys) were more appropriate contexts to respond to research questions. To illustrate this, analysis of Understanding Society data became voluntarily constrained to a sample of people seeking employment, rather than the wider sample. In addition to such respondents being particularly relevant, conducting analyses amongst a population of people not seeking employment (e.g. happily employed) would have affected results. It is difficult to accurately assess how useful SNS are as a tool to gain information regarding job vacancies when a significant proportion of the sample population are not looking to change, or attain, jobs.

3.7.2 Primary analysis

Analyses broadly pertaining to similar themes amongst each of the three primary case study populations (with some contextual variation) meant that research questions were tested thoroughly using data pertaining to each context. However, an unintended consequence of this plausibly robust analytical approach occurred in some divergence of findings. Findings are not uniform across these case study groups, which renders reduction into 'key findings' particularly difficult.

Chapter 4 – Oxford Internet Surveys (OxIS) analysis

4.1 Introduction

Analyses presented in Chapter 4 interrogate data from the Oxford Internet Survey (OxIS) 2013 (Dutton and Blank, 2013). The dataset is rich in variables describing internet behaviours related to job-seeking, social capital, and human capital (for further details, see 3.5.2 'Oxford Internet Surveys'). The chapter examines the contribution of SNS use in the context of employment outcomes (Research Question A) and explores the role of structural disadvantage within these uses (Research Question B). The chapter therefore provides a contribution towards both of the project research questions, and the wider body of literature reviewed in Chapter 2 that informed the research questions.

4.1.1 Literature overview

Social capital is a distinct form of capital that interacts with the other forms of capital (Bourdieu, 1986). Through the lens of employment outcomes, it is a component of human capital: when developed and nourished, information received through contacts can be critical to gaining new positions (Granovetter, 1973; Lin, 1999). Possession of strategic connections leads to positive performance evaluations and greater compensation (Burt, 2004). Strategic connections are likely to be composed of weak ties, based on the principle of homophily (McPherson *et al*, 2001). The relative value of weak ties depends on place within the wider structure, as strong ties of privileged individuals are also likely to be valuable (Lin and Dumin, 1986).

In the networked age SNS represent a tool that individuals can use to circumvent traditional barriers to the development of a network of weak ties. With application, these ties can provide invaluable information for the advancement of careers (Rainie and Wellman, 2012). Research linking social capital use via SNS to employment outcomes finds mixed evidence regarding the extent that it can cultivate bridging social capital (Shpiegalman and Gill, 2014) and support employment outcomes by using weak ties in the job-search process (Gee *et al*, 2017). Research into internet use and outcomes amongst the online population also identifies traditional, structural barriers towards productive internet use (the 'second-level digital divide' (Hargittai, 2008a)) that mark experience of offline inequality.

In the light of such mixed claims, this chapter seeks to provide new evidence on the role of online social capital in employment outcomes. All analyses presented within this chapter are conducted within a reduced sample universe. The whole sample universe consists of 2,053 respondents. The reduced sample excludes respondents who, at the time of data collection, were not current users of the internet, reducing the sample size to 1,430. In most analyses, survey weights provided within the OxIS 2013 data file are applied to mitigate biases resulting from under- or over-representation of groups within the internet-using sample; this should imply that the results from the reduced sample provide a reasonable basis for inference to the internet-using population of the UK in 2013.

4.1.2 Research questions addressed

A description of analytical themes and the research questions that each addresses are provided in this sub-section for reference. Table 4.1 restates Thesis research questions outlined in *2.7.2*.

Research Question A: Does SNS use benefit career management?	**Research Question B: Who benefits from the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	**B1)** Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	**B2)** Who benefits from the potential of the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	**B3)** Is there an uneven distribution of positive, career-outcome benefits from weak tie social capital use?

Table 4.1: Thesis research questions.

Table 7.2 provides further detail on the three aforementioned analytical themes in context of career management; SNS use and social capital, an exploration of the second-level digital divide, and the closeness of ties. Grouped into these themes, topics of individual analyses are detailed in relation to the research question that they address. A summary of the way indicators are operationalised in models is included.

Analytical grouping	Analysis question	Modelling strategy	Research question(s) addressed
A: Benefits of SNS use	**(A1)** Does SNS use provide a career management boost?	3 models: SNS use, instant messenger use, and both predicting gaining a job online	Research Questions A1-3
	(A2) Does frequency of SNS use provide a career management boost?	1 model: Frequency of SNS use predicting gaining a job online	Research Questions A1-3 (in conjunction with Analysis A1)
	(A3) Does SNS use predict wider internet activity that improves social and human capital?	4 models: SNS use predicting four types of productive internet use	Research Questions A1-3
B: Distribution of effects or benefits of internet use	**(B1)** Does skill level predict gaining rewards from online career management?	2 models: Two indicators of internet skill predicting gaining a job online	Research Questions B1-2
C: Who uses the internet productively?	**(C1)** What characteristics predict beneficial internet and SNS use? Are they reflective of the research literature?	2 models: Characteristics of respondents predicting gaining a job online and SNS use	Research Questions B1-2
	(C2) What characteristics predict beneficial internet use? Are they reflective of the research literature?	4 models: Four indicators of productive internet use predicted by characteristics of respondents	Research Questions B1-2

Table 4.2: Analytical structure details and research questions addressed.

Analyses within this chapter address all project research questions except B3, which requires detailed information on personal ties. Chapters 6-8 provide relevant coverage.

4.2 Survey results

4.2.1 Sample characteristics (demographic)

Table 4.1 provides a summary of socio-demographic variables employed in analyses. These markers also signpost differentiated experiences of SNS in a career management context, which are summarised in this sub-section.

Original variable name and description	Category	% of unweighted sample (freq.)	% of weighted sample (freq.)
Gender (original)	Male	42.10% (602)	49.90% (714)
	Female	57.90% (828)	50.10% (716)
	Missing data	0% (0)	
Highest educational attainment (recoded version operationalised in analysis)	Higher education	31.26% (447)	30.65% (438)
	Further education	16.43% (235)	17.45% (249)
	Secondary education	38.53% (551)	39.01% (557)
	No qualifications	13.64% (195)	12.89% (184)
	Missing data	00.14% (2)	
Ethnicity (recoded version operationalised in analysis)	Asian	4.27% (61)	6.42% (91)
	Black	3.64% (52)	3.97% (56)
	White	90.21% (1,290)	88.14% (1,251)
	Other	1.12% (16)	1.46% (21)
	Missing data	0.77% (11)	
Urban density (recoded version displayed, and operationalised in analyses)	Urban	84.55% (1,209)	86.83% (1,242)
	Rural	15.45% (221)	13.17% (188)
	Missing data	0% (0)	
Age: Mean = 45.73 **(weighted = 41.46)|** Std. Dev. = 16.92 **(weighted = 16.83) |** Range = 16-90 **(weighted = 14-90) |** Skewness = .22 **(weighted = .38)**			
Occupational prestige: Mean = 45.46 **(weighted = 44.70) |** Std. Dev. = 13.81 **(weighted = 13.74) |** Range = 22-70 **(weighted = 22-70) |** Skewness = .15 **(weighted = .23)** Missing = 7.33% **(105)**			

Table 4.3: Demographic characteristics of respondents. Subsample of current internet users (n = 1,430), weighted and unweighted statistics provided. Variable names and whether these are original formats provided in data, or recoded versions when operationalised in analyses (first column).

The sample contains a small majority of women (58%). In addition to well-publicised inequalities experienced in employment outcomes to men – for example the full-time median hourly pay gap (Brynin, 2017) – the literature suggests women have less access to potentially beneficial weak ties (McPherson and Smith-Lovin, 1982; Lutter, 2015). Women are also found to use SNS for building weak tie social capital less than men (Hargittai and Hsieh, 2010; Masman and Usluel, 2011), although sex does not appear as a demographic marker relating to other aspects of the second-level digital divide in literature reviewed.

Education level is measured via highest educational attainment within the data. The raw form of this variable contains four categories; no qualifications, secondary education, further education and higher education. In all analyses this variable is recoded into a dummy variable (higher education/other) which measures the difference that having a degree makes towards given outcomes. This recode also eliminates a potential cohort effect, as after 1973 (in England and Wales) children were required to remain in school until the age of 16 (Cowan *et al*, 2012), meaning leaving school without qualifications became less common. Education level is centrally important to employment outcomes. For example, it best predicts wage levels in the UK (Howard *et al*, 2014; Naylor *et al*, 2015). Education level consistently predicts productive internet use within digital divide literature (e.g. Robinson *et* al, 2003; Wei and Hindman, 2011). Some evidence finds a stratification of SNS use by parental education (Hargittai, 2008c), and studies exploring the interaction between social capital use and education in the context of employment outcomes find differential benefits of weak tie use (e.g. Ericksen and Yansey, 1980). Within this sample, 31% have a Higher Education qualification.

Black and minority ethnic (BME) groups in the UK are likely to be under-represented within the sample. 91% of respondents identify as 'white', with other groups totalling around 9% of valid responses. The last census of England and Wales records the population as 14% BME (ONS, 2012). Although weights are applied to multivariate analyses, a binary indicator of ethnic status (white/BME) was used in analyses. This level of measurement is regarded as reductive in measuring ethnic differences (Stayman and Deshpande, 1989), but in practice many studies employ such as measurement through a lack of case numbers (e.g. Kramarz and Skans, 2014; Matzat and Sadowski, 2015). In the UK, ethnicity is a significant marker of labour market inequality as illustrated for example by the ethnic median hourly full-time pay gap (Longhi and Brynin, 2017). Ethnic minority groups have been found to have access to less social capital (Verhaeghe *et al*, 2015), and ethnicity has been identified as a marker of differential SNS use (Hargittai, 2008c).

Urban density is a factor which receives relatively little attention in second-level digital divide literature. In public discourse, slower broadband speeds for rural residents is a well-articulated issue. Ofcom (2018) research finds that rural speeds are still slower for rural residents, which could impact upon users' ability to use the internet as productively as urban counterparts. Autonomy of use is defined by Hargittai (2008a) as a key factor of a non-binary digital divide, and these patterns suggest that urban/rural locality could have an influence upon autonomy of use. Urban density is operationalised as an urban/rural binary variable in analysis. 15% of respondents live in more rural areas. This binary categorisation is derived from separate classifications for Scottish postcodes, and postcodes for England and Wales.

Age is hypothesised to be an important axis of the second-level digital divide. The theory of 'digital natives' (Prensky, 2001) argues that older generations lack the natural capacity to exploit productive capabilities of the internet compared to those for whom digital technologies were a ubiquitous aspect of their formative years. The average age of this sample is 46, and the distribution has a slight positive skew. The dataset therefore represents the spread of age across the general UK population well, and is suitable for testing the digital natives hypothesis, although given this project is primarily concerned with the working-age population, perhaps younger people are under-represented.

4.2.2 Dependent and independent variables

The variable most commonly operationalised as a dependent variable in analyses indicates whether respondents have found a job via an online source previously, and is detailed in 3.5.2.3. Table 4.3 summarises a number of other measures that are sometimes used as dependent or independent variables. The measures, are organised according to the modal analytical theme that they are operationalised in; benefits of SNS use (Theme A), distribution of effects or benefits of SNS use (Theme B), who uses the internet productively? (Theme C). Frequencies of variables provided are weighted, based upon analytical operationalisation.

Analytical theme	Variable (Operationalisation)	Analyses used in	Frequencies and structure (weighted)
A: Benefits of SNS use	Uses instant messenger (independent)	A1	0 = No **26.89%** (385) 1 = Yes **72.70%** (1,040) . = Missing **0.41%** (6)
	SNS user (independent + dependent)	A1, A3, C1	0 = No **21.14%** (302) 1 = Yes **78.86%** (1,128)
	How often checks or updates SNS profile (independent)	A2	. = Never **38.41%** (549) 1 = <Monthly **13.59%** (194) 2 = Monthly **6.87%** (98) 3 = Weekly **12.52%** (179) 4 = Daily **28.60%** (409)
B: Distribution of effects or	Confidence in judging reliability of information online (Higher = more confidence; independent)	B1	1 = **4.00%** (57) 2 = **14.11%** (202) 3 = **61.57%** (881)

benefits of internet use			4 = **18.50%** (265) . = Missing **1.83%** (26)
	Confidence in technical ability (Higher = more confidence; independent)	B1	Mean = **11.61** Std. Dev. = **5.79** Range = **0-20** Skewness = **-.45** Missing = **0.28%** (4)
C: Who uses the internet productively?	Found information about health or medical care online before (dependent)	A3, C2	0 = No **31.04%** (444) 1 = Yes **68.34%** (977) . = Missing **0.61%** (9)
	Found acquaintance online before (dependent)	A3, C2	0 = No **57.54%** (823) 1 = Yes **41.13%** (588) . = Missing **1.34%** (19)
	Found out about an event online in the first instance (dependent)	A3, C2	0 = No **37.13%** (531) 1 = Yes **62.62%** (895) . = Missing **0.26%** (4)
	Checked a fact online before (dependent)	A3, C2	0 = No **34.12%** (488) 1 = Yes **65.07%** (931) . = Missing **0.81%** (12)

Table 4.4: Dependent and independent variables operationalised in analyses. Column 3 = structure and whether this operationalisation is original or a recoded version. N = 1,430.

Variables relating to whether respondents have found health or medical advice online, and checked a fact online were dichotomised. They are originally structured as Likert scales. However, given this research is interested in differences in internet use, recodes which separate respondents who carry out a certain activity from those who do not provide more meaningful sites of analysis than variables denoting gradations of frequency.

The use of an 'Instant messenger' could apply to a range of platforms that facilitate communication between people. They are not necessarily connected to social networking sites. Applications such as WhatsApp connect individuals through mobile phone numbers, rather than SNS, and are essentially text messaging services that use an internet connection (Svetlik, 2019). Facebook Messenger is similar in terms of functionality, but operates as an extension to the SNS platform (Facebook, N.D.) where users can talk away from the public platform. WhatsApp and Facebook Messenger are the two most popular instant messenger applications globally (Statista, 2019). The instant messenger use variable within OxIS data is therefore only a partial proxy of a type of SNS use, which also represents use of platforms more suitably termed 'social media' (Boyd and Ellison, 2007). It is operationalised presently because it is taken to represent a different mode of SNS use to other indicators, however. Using the example of Facebook, users rarely make requests to single users for information via the main application, but typically broadcast requests to selected groups, or all contacts (Ellison *et al*, 2014). Messenger is a more frequent mode of making resource requests direct to an individual (Wee and Lee, 2017).

Occupational prestige is an occupational ranking measure included within the data set. Rankings relate to current jobs, or if a respondent is not working at the moment (e.g. unemployed, retired, student) their last job. Those without previous jobs are classified as missing cases.

Before operationalising these variables in multivariate analyses levels of collinearity were tested. All independent demographic control variables were first tested via factor analysis. This revealed two latent factors that the variables loaded on to. These latent factors did not produce uniqueness statistics low enough to cause concern about collinearity. A Kaiser-Meyer-Olkin Test produced a result of 0.77, which is below the threshold for suitable inclusion of the factors in modelling, and therefore collinearity is not a concern amongst variables selected in these data (Crane *et* al, 1991). The variable denoting frequency of SNS use was not included in these tests as it is a recoded version of absolute use.

4.3 Multivariate analysis

Multivariate analyses are presented and discussed in relation to project research questions (see 4.1.2) over two sections. The first section relates to Research Question A, investigating the benefits of SNS use on employment outcomes. The second and third section address Research Question B, exploring population distributions of any effects or benefits.

4.3.1 Theme A: Benefits of SNS use

Whether respondents have gained employment via the internet is the most frequent site of analysis, both in this section and in respect of all results reported in this chapter. This is due to the parsimonious way in which this variable covers the question of how useful the internet is for getting jobs, and because it can be analysed in conjunction with social capital variables to address the assumption central to Rainie and Wellman’s (2012) work. That is, that the internet – with focus on SNS – is transformative in the context of career attainment. Ease of forming and maintaining connections to social resources could break down barriers that traditionally have been an obstacle to management of a heterogenous weak tie network. As an outcome representing attainment, employment is a conventional measure (e.g. Breen, 2004; Griffiths and Lambert, 2015).

In Table 4.5, Analysis A1 test the effect of SNS use on the likelihood of respondents having secured a job which they saw advertised online, controlling for demographic factors. The models employ two variables representing SNS use; whether respondents use SNS, and whether respondents use instant messenger to predict gaining a job online (see Table 4.4 for independent variable details, and 3.5.2.3 for dependent variable details). Both independent variables are modelled together (model 3) to test effects net of each other.

DV = gained job online	Control model	A1 (model 1)	A1 (model 2)	A1 (model 3)
Age	-.04***			
Degree	1.05***			
Female	-.22			
BME	-.43			
Rural	-.34			
Occupational prestige	.01*			
SNS use		1.33***		1.08**
Instant messenger use			.94***	.41
Pseudo r2 =	.10	.13	.12	.14
BIC =	1534	1499	1514	1503

Table 4.5: Analysis A1, predicting gaining a job which was found via an online advert. Controls in column 2 consistent across models 1-3. Independent variables; use of SNS (model 1), use of instant messenger (model 2), use of SNS + instant messenger use (model 3). N = 1,307.

The control model finds that age has a significant negative effect on gaining jobs online, which correlates with the theory of digital natives (Prensky, 2001) – that younger internet users should be more skilled internet users, and therefore outcomes from use should be less productive. Education also positively predicts the dependent variable, which is consistent with the second-level digital divide for similar reasons (Hargittai and Hinnant, 2008). Further, occupational prestige also has a significant and positive effect, therefore suggesting that jobs found online are of a relatively high quality. Occupational prestige is subsequently controlled for in all further analyses operationalising gaining jobs online as dependent variable (throughout the chapter). Insignificant factors are kept in due to identification in the research literature as important to the themes of analysis.

SNS use is found to be a positive and significant predictor of getting a job online in Model 1, as is instant messenger use in Model 2. When independent variables are tested net of each other in model 3, instant messenger use becomes insignificant, suggesting that perhaps the effect of SNS use is proxied through messenger use in model 2.

Analysis A2 extends Analysis A1 to take into account frequency of SNS use. Therefore A2 uses a sub-population composed of SNS users as the site for analysis, in predicting gaining a job online.

DV = gained job online	Control model		A2 (model 1)
Age	-.03***		
Degree	.85***		
Female	-.22		
BME	-.50		
Rural	-.36		
Occupational prestige	.02*		
Frequency of SNS use		Monthly:	.23
		Weekly:	.80**
		Daily:	.79**
BIC =	1127		1128
Pseudo r2 =	.07		.08
Key: ˡ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 4.6: Analysis A2. Logistic regression predicting gaining a job which was found via an online advert. Independent variable = Frequency of SNS use (reference category = Less than monthly). N = 735 (SNS users only). Controls consistent across control model and model 1.

Analysis A2 finds significant positive association between more frequent uses of SNS and gaining a job online. Combined with results of Analysis A1, findings suggest that SNS use grants a bonus to likelihood of gaining more prestigious online jobs. Amongst SNS users, greater frequency of engagement with the platforms has a positive effect on likelihood of getting such jobs.

Analysis A3 (Table 4.7) investigates a potential relationship between SNS use and the development of human and social capital via wider internet use. This analysis achieves two objectives. First, unpacking the proposed relationship between SNS use and human and social capital development (Rainie and Wellman, 2012). Second, should significant and positive association be found, it would suggest the existence of a general population of productive internet users, who experience preferential outcomes in the form of more prestigious jobs advertised online. This would imply that the second-level digital divide is a factor of influence within career management in context of SNS and the internet more generally.

Four tests within Analysis A3 employ SNS as an independent variable predicting separate productive internet uses. Model 1 employs as the dependent variable an indicator representative of a potential boost to networks that internet use (or, within this, SNS use) theoretically provides – the ability to reactivate fading or lost weak ties. This indicator measures whether respondents have discovered an old acquaintance online. Model 2 operationalises as dependent variable an indicator of whether respondents have heard about an event online in the first instance. This indicator does not fit as neatly as a proxy for social capital, because attendance at an event does not imply that social capital will be boosted, although it could be potentially – for instance, attendance at an event could provide unique information that benefits in a career management sense, but this is not guaranteed.

Influence of SNS use on whether the respondent has used the internet to check for a fact is the subject of Model 3. This dependent variable is taken as an indicator of human capital. Finally, Model 4 employs a dependent variable denoting whether respondents have used gained health or medical advice online. As with the dependent variable in Model 3, this outcome is viewed as being generally 'productive' – potentially contributing to human capital through becoming more informed, although not definitely having a direct career impact. Within Table 7 key control model statistics predicting each dependent variable net of factors listed in Table 4.6 are provided sequentially for reference.

	Control: Found acquaintance online	**Model 1**	**Control: Found event online**	**Model 2**	**Control: Checked fact online**	**Model 3**	**Control: Found health advice online**	**Model 4**
SNS user		**1.98*****		**.90*****		**.24**		**.56*****
BIC =	2137	**1998**	2046	**2013**	2016	**2021**	1971	**1964**
Pseudo r2 =	.02	**.09**	.05	**.07**	.03	**.03**	.02	**.03**
N =	1,398	**1,398**	1,411	**1,411**	1,408	**1,408**	1,410	**1,410**

Key: ' p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 4.7: Analysis A3. Logistic regressions employing SNS use to predict previous activity online: Finding an acquaintance (model 1), finding out about an event in the first instance (model 2), checking a fact (model 3), finding health or medical advice (model 4). Key control model statistics predicting each dependent variable net of factors listed in Table 4.6 control model included.

Model 1 finds that SNS use has a significant and positive effect on whether respondents have found an acquaintance online, implying that SNS are a useful tool for weak tie social capital maintenance, as indicated by the literature. Model 2 similarly finds a significant boost of SNS use on hearing about online events. The two findings chime with the logic that SNS are a useful tool for maintaining lightweight contact with individual connections (Boyd and Ellison, 2007) and are platforms with high levels of organisational presence – such as Twitter and Facebook (Stephenson *et al*, 2018) - both in turn potential creators of online event pages.

Model 3 finds no effect of SNS use on whether respondents had used the internet to check a fact. However model 4 does find a significant and positive effect of SNS use on occurrences of receiving health or medical information via the internet amongst the sample. The significant effect in Model 4, but not in Model 3, might reflect the use of social media to communicate with patients by health professionals (Rolls *et al*, 2016) and other virtual health communities that are characterised by communication between members of the lay public (Huh *et al*, 2013).

Analyses addressing the question of whether SNS use provides additional career benefits lead to relatively unambiguous conclusions in this particular data set. SNS use is found to positively predict successfully finding a job online, as does frequency of SNS use. Such jobs in turn are found to be more prestigious. Analyses predicting potential social capital benefits of internet use are also found to be boosted by SNS use, adding some detail to the relationship between SNS use and online jobs. This detail suggests that social capital could be a factor influencing attainment of more prestigious online jobs, although data does not exist presently to test whether bridging social capital – associated with weak ties – is the driving factor, or to delve further into this potential relationship. Limited evidence relates human capital boosting behaviours online positively with SNS use. Within this mixed evidence, it is suggested that if SNS use does provide indirect benefits towards career outcomes via human capital accumulation, these are not uniform and depend on the measure of human capital.

4.3.2 Theme B: Distribution of effects of internet use

The previous section presents evidence in support of Rainie and Wellman (2012) – that SNS are a transformative tool for attainment - in the context of career management. The present section, therefore, tests for implications of the second-level digital divide, as identified within the research literature (e.g. Hargittai, 2008a). The distribution of benefits in the literature broadly reflects a mirroring of structural inequality within the online sphere, whereby traditional barriers to occupational attainment prevent or mitigate online gains. Markers of these barriers explored within this section are age, education, sex, race and urban residence. A summary of second-level digital divide evidence pertaining to these markers it provided in 4.2.1.

Prior to tests exploring demographic barriers, two non-demographic factors that should – based upon the assertions of the second-level digital divide – help explain differentiation in uses of and outcomes from internet use are modelled to predict attainment of a role that has been advertised online. These factors represent self-assessments by respondents of their critical skill and their confidence in using technology.

Self-assessment of critical ability is in the context of assessing sources of information online. Respondents were asked how confident they are in judging the reliability of online content, and to rate on a scale of 1-4. This scale is in the format of a traditional 5-point Likert scale, with the middle response option removed. Critical ability is often associated with education level (Pardue, 1987; Fero *et al*, 2009), although the gamma statistic for the association between the critical skill variable and education level is .27. This implies that although the two are related, critical skill is not a direct proxy of education level.

Respondents' confidence in using technology is measured via a 21-point scale (0-20), which appears to be derived from responses to a series of questions that ask respondents how confident they are in performing a series of everyday online tasks (e.g. 'how confident do you feel that you would be able to download and save music (MP3s)'). Unlike critical ability, theory does not point to one single factor which should have a key influence on confidence with technology, although the theory of digital natives (Prensky, 2001) appears particularly relevant. Ubiquitous integration of internet-connected technologies in daily lives within formative years should logically produce greater confidence in use. The Pearson's correlation between age and confidence in technology in this data is 0.42, which implies quite a strong relationship between the two factors, but again neither is a direct proxy of the other.

Confidence in using technology and critical ability online were separately modelled as independent variables predicting attainment of a job that was found online, summarised in Table 4.8 (Analysis B1).

DV = Gained job online	**Control model**		**B1 (model 1)**	**B1 (model 2)**
Critical ability online		Not confident at all:	1.27ᵻ	
		Not confident:	-.08	
		Fairly confident:	-.08	
Confidence with using technology				.05**
BIC	1521		1525	1503
Pseudo r2 =	.12		.11	.12
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 4.8: Analysis B1. Logistic regression models predicting gaining a job which was found via an online advert. Independent variables: Critical ability with reference to confidence judging validity of materials online (reference category 'very confident'; model 1), confidence with using technology (metric variable, higher score equals more confidence; model 2). Both models net of controls listed in Table 4.6. N = 1,285.

In Model 1, critical online ability is operationalised as a categorical variable. Results show that respondent self-rated ability to critically assess validity of online materials does not significantly impact gaining a job online. Model 2 finds a boost in likelihood of securing a job advertised online associated with higher levels of confidence in using technology. In summary, results of Analysis B1 suggest that confidence in using technology positively affects gaining a more prestigious job advertised online, and that critical ability does not have an effect. This is perhaps surprising, given the close relationship between critical ability and educational attainment. Educational attainment is found consistently within research literature to predict productive internet and SNS use via the proxy of internet skill level (Hargittai and Hinnant, 2008; van Deursen and van Dijk, 2014). The results perhaps separate out components of online skill, which would suggest that confidence in using the means to access SNS and the wider internet (i.e. hardware), is more important than ability to understand materials once online. The results tentatively support the narrative that productive internet use is mediated by ability to utilise the medium. The next analyses further explore the role of demographic factors in predicting differentiated uses.

4.3.3 Theme C: Who uses the internet productively?

Analyses presented so far have found that jobs advertised online were generally of better quality, and that SNS use positively affects probabilities of having secured such a job. The results detailed in Table 4.9 (Analysis C1) compare the characteristics of both SNS users and those who get jobs advertised online in order to explore whether the results are showing that a relatively savvy, or skilled, population use SNS, who in turn are naturally more eligible for online jobs. Different results would imply that SNS use is providing a genuine boost to career management, rather than incidental.

	C1 (model 1, DV = gained job online)	**C1 (model 2, DV = SNS use)**
Age	-.04***	-.06***
Degree	1.03***	-.05
Female	-.23	.16
BME	-.48ᶦ	.66*
Rural	-.31	.07
Pseudo r2 =	.09	.16
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 4.9: Analysis C1. Characteristics of respondents predicting attainment of a job advertised online (model 1), and SNS use (model 2). N = 1,414.

Although age (negatively) and degree-level educational attainment (positively) are found to significantly effect attainment of a job advertised online, educational attainment is not found to be a factor predicting SNS use.

Importantly for findings related to career management, these results suggest that SNS use provides a genuine bonus. Education level could still be a factor in how SNS are used to cultivate social capital and to access it for informational, career management purposes, but this cannot be explored with current data. Sex and urbanisation of home address also have no effect. Another difference is however identified in relation to ethnicity. Those from BME backgrounds are suggested to have less chance of obtaining an online-advertised job (P-value approaching significance), but are significantly more likely to use SNS. Results relating to ethnicity add further weight to the idea that SNS-using and online job-attaining populations are different. It should be noted however that the ethnicity indicator operationalised is of relatively poor quality. The suggestion that BME use of SNS particularly differs to white use should be explored further using better data that accounts for gradations within ethnic minorities, because this community is not a homogenous bloc (Williams, 1996).

Lastly, Analysis C2 (Table 4.10) explores relationships between demographic factors, and the human/social capital factors that were included in Analysis A3. In those models (Table 4.7), SNS use was found to have a significant and positive effect on hearing about events online in the first instance, on reconnecting with an acquaintance online, and on gaining health or medical information online. SNS use was not found to impact online fact-checking. These final models establish whether demographic factors reflect second-level digital divides (as established within the research literature) with regards to these human and social capital boosting behaviours. Additionally, for those behaviours that were shown to receive a boost from SNS use, demographics are compared with those describing SNS use (Analysis C1, model 2; Table 4.9) to determine whether populations are different (implying that SNS provides a genuine bonus), or similar (implying the boost is incidental).

	Model 1 (DV = found acquaintance)	Model 2 (DV = found event)	Model 3 (DV = checked a fact)	Model 4 (DV = found health information)
Age	-.02***	-.02***	-.01***	.00
Degree	.39**	.97***	.78***	.46**
Female	.11	-.14	-.21	.57***
BME	.08	-.72**	-.30	-.22
Rural	.18	.14	.47*	.23
Pseudo r2 =	.02	.05	.03	.02
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 4.10: Analysis C2. Four social/human capital factors predicted by demographic factors. Dependent variables; Finding an acquaintance (model 1), finding out about an event in the first instance (model 2), checking a fact (model 3), finding health or medical advice (model 4). N = 1,410.

Regarding identification of second-level digital divides, each Model (1-4) within Analysis C2 finds degree-level educational attainment to significantly and positively effect each respective use of the internet modelled – reconnecting with acquaintances (model 1), finding out about an event online in the first instance (model 2), checking a fact (model 3), and getting health or medical information (model 4). Age is found to have a significant and negative effect on the likelihood of occurrence of all behaviours, except getting health or medical information (a cohort effect could mask age effects in Model 4, if the people most likely to require medical information are older). Both education and age therefore appear similarly important aspects of the second-level digital divide in the context of activity affecting career management. Evidence relating to the other demographic factors measured (sex, race, urbanisation of home postcode) is inconclusive on the whole, suggesting these factors are not markers of the second-level digital divide.

Analysis C1 – predicting SNS use – also found age to significantly and negatively influence the dependent variable. However, the absence of an effect for education in Model 1 (Analysis C2) provides evidence that the population of SNS users is different to populations utilising the internet to improve social and human capital. SNS use is instrumental in providing these career management benefits, according to these OxIS analyses.

4.4 Conclusion

Results presented in this chapter suggest distinct and consistent benefits to career management stemming from SNS use which are gained disproportionately by certain demographics. The chapter provides a contribution linking several related areas of research literature in response to the claims of Rainie and Wellman (2012) on the transformative nature of SNS for career attainment. The evidence found in response supports their findings with regards to SNS being a useful tool in the career management repertoire, but suggests their work is too optimistic in its assessment of how universal those benefits are. Structural barriers which Rainie and Wellman claim are mitigated by transformational technology are nevertheless identified as consistently significant factors affecting outcomes amongst internet users in the contemporary UK.

Analysis suggested that jobs which are found online are likely to be more prestigious. SNS use, frequency of SNS use and messenger use were all found to significantly predict a greater likelihood of obtaining such jobs. These findings support the notion of the importance of social capital in career management, although do not identify specific processes of activation of contacts. Greater frequency of SNS use does suggest however that more time spent maintaining social ties produces informational resources that can be beneficial to career management - at odds with Matzat and Sadowski's (2015) study that found no such link. Data was not available to assess the theoretical assertion that weak ties produce particularly beneficial information (Granovetter, 1973), which in an SNS context has mixed support in research literature.

SNS use is also found to predict specific internet usages that could benefit career management via boosting social and human capital, such as finding out about events. This supports Rainie and Wellman's (2012) visualisation of how networked resources can be an informational starting point for people who then act upon information to improve their skills, such as studying a course.

Validity of linkages connecting SNS use to enhanced career-related outcomes are strengthened by analysis of the general SNS-using population versus those that get online jobs, or use the internet productively. Characteristics of the SNS-using population are found to be significantly different to the characteristics of populations associated with behaviours and outcomes which SNS predicts, ruling out the possibility of incidental correlations.

Instead what is identified through analyses of populations is a sub-population of internet users who are able to utilise the internet and SNS productively in a career management context. This is identified through a main outcome of attainment of a job advertised online, as well as other outcomes denoting capital boosts. The identification of internet users not willing or able to generate such outcomes are of particular interest to the second-level digital divide (Hargittai, 2008a) literature, and provides a rebuttal to Rainie and Wellman (2012). This population is identified as lacking the skill to assess the reliability of information online, and are generally unconfident with using technology. Both limitations are identified as barriers towards utilisation of the internet in the literature. First, ability to navigate the internet towards specific informational outcomes is identified as a specific barrier towards productive use by Hargittai (2008b), and is deemed an aspect of skill. This author had earlier identified with colleagues' education level influence internet use skill, a reflection of the same barrier that traditionally inhibits people from acting upon information in print (Robinson *et al*, 2003). Second, lack of confidence is seen as a generational consequence, disproportionately experienced by older people (Prensky, 2001). Education and age are consistently found to be predictive factors of productive internet use, and of associated outcomes in present research.

Other demographic factors tested within analyses that are identified in second-level digital divide literature as markers of online inequality are not found to play a significant role. Urban/rural status , despite issues with slow broadband speeds in rural UK areas (Ofcom, 2018), which logically effect autonomy of use (Hargittai and Hinnant, 2008), is not found to be a factor influencing productive internet use. Gender differences in use and outcomes are not found with any consistency either, despite inequality experienced by women in the labour market (e.g. Brynin, 2017) and in levels of workplace social capital (McPherson and Smith-Lovin, 1982). Women have also previously been found to be less likely to use SNS to boost weak tie social capital (Masman and Usluel, 2011). Ethnicity is similarly a marker of labour market inequality (e.g. Longhi and Brynin, 2017), of employment outcomes related to social capital (Verhaeghe *et al*, 2015), and of differential SNS use (Hargittai, 2008c). However it is not identified with any consistency as an influential factor in present analyses. It should be noted that the reduction of ethnicity to a binary variable as a matter of analytical expediency could have affected findings.

Chapter 5 presents analysis of the secondary data source Understanding Society. Having identified relatively broad gains in employment-based outcomes through SNS use in Chapter 4, the next chapter provides greater focus on types of employment outcomes through analysis of a job-seeking sample. A greater number of job-search indicators allows for comparison with jobs advertised online, adding richer detail to findings presented in Chapter 4.

Chapter 5: Understanding Society analysis

5.1 Introduction

Chapter 5 presents results from analyses linking together multiple waves of Understanding Society (University of Essex, 2018a) data. Analyses focus on unemployed respondents actively looking for work in waves 4 or 5 (2012-15), tracking their progress into wave 6. Therefore employment outcomes are viewed in context of what job-seeking respondents did in prior job searches. Additionally, analysis of Understanding Society data allowed for inclusion of a greater range of job-search techniques in analyses (in addition to searching online), in context of a more diverse set of employment outcomes, measuring job attainment and job quality. This ensures extensive coverage of how SNS, social capital and internet use influence working outcomes.

These analyses address most aspects of Research Question A (does SNS use benefit career management?), and partially Research Question A2 (the role of weak ties within SNS-based career management). Neither the Oxford Internet Surveys (OxIS, see Dutton and Blank, 2013) nor Understanding Society provide any indicators that can reasonably be used as proxy indicators of weak tie relations, but network homogeneity indicators do exist in Understanding Society, and these can be linked to the 'strength of weak ties hypothesis' (Granovetter, 1973). Analyses addressing aspects of Research Question B (the role of structural disadvantage within career management in the context of SNS) are not attempted with this data. This is due to a lack of good indicators of internet use, compared to those employed in Chapter 4. Any such analyses attempted with Understanding Society data would not add to what is presented in Chapter 4.

Wider bodies of literature that this chapter contributes to concern the efficacy of social capital and SNS use, as well as diversity of network characteristics, within career management. Use of contacts within job seeking can be critical to acquiring new positions (Granovetter, 1973; Lin, 1999). Weak ties, rather than strong, are most likely to have access to original information that can be used to the worker's advantage (Burt, 2004). This theory is extended to SNS, which break down traditional barriers that inhibit the development of useful contacts (Rainie and Wellman, 2012). It is often asserted that individuals cluster together on the basis of shared characteristics and life experiences (e.g. McPherson *et* al, 2001). The homophily principle has meaningful implications for career management. For disadvantaged groups, a lack of access to non-disadvantaged connections within employment markets theoretically reinforces disadvantage, given the importance of connections in securing employment. Homophily is a concept separate to the ways in which access to weak ties are envisaged as being important for career management by Granovetter (1974), although there appears to be considerable conceptual overlap. Weak ties are not by definition heterophilous, but it is likely that a well-developed network of weak ties contains diversity.

Analyses presented within this chapter are conducted amongst a subsample of Understanding Society respondents. 1824 respondents were unemployed and actively looking for work in Waves 4 (data collection 2012-14) or 5 (data collection 2013-15), and are also present in Wave 6 (data collection 2014-16). Although data collection for any given annual wave of the survey can be spread over up to three years, survey respondents individually are contacted annually, approximately one year after their last interview. All variables referred to in this chapter are taken from the Wave 6 individual responses data set (‘f_indresp’) unless otherwise stated. This is because many indicators of interest do not occur in Waves 4 or 5 when respondents were looking for work (for further details, please see 3.5.1 Understanding Society).

5.2 Survey Results

5.2.1 Sample characteristics

Table 5.1 provides weighted and unweighted data on sample characteristics. Although weighted frequencies are utilised in analyses, unweighted properties are provided to give a fuller picture of respondents within the universe. Weighted frequencies do not equal whole numbers and are subsequently rounded, as are percentages. All indicators of sample characteristics are taken from Wave 6.

Variable name and description	Category	% Unweighted (freq.)	% Weighted (freq.): Rounded
Gender (original)	Male	50.66% (924)	55% (885)
	Female	49.34% (900)	45% (727)
	Missing data	0% (0)	0% (0)
Highest educational attainment (recoded version operationalised in analysis)	Higher education	24.45% (446)	24% (380)
	Further education	16.45% (300)	15% (245)
	Mandatory education	51.48% (939)	54% (875)
	Missing data	7.62% (139)	7% (112)
Ethnicity (recoded version operationalised in analysis)	White British	66.01% (1,204)	82% (1,325)
	White other	3.84% (70)	3% (53)
	Mixed	3.02% (55)	1% (23)
	Asian	13.43% (245)	5% (78)
	Black	7.73% (141)	3% (52)
	Other	0.88% (16)	1% (12)
	Missing data	5.10% (93)	4% (70)
Urban density (original)	Urban	82.68% (1,508)	81% (1,313)
	Rural	17.32% (316)	19% (299)
	Missing data	0% (0)	0% (0)
Disability: Long standing impairment, health problem, or disability (original)	Yes	27.80% (507)	31% (495)
	No	72.09% (1,315)	69% (1,117)
	Missing data	0.11% (2)	0% (0)
Country of residence (original)	England	80.54% (1,469)	82% (1,316)
	Wales	6.20% (113)	6% (97)
	Scotland	7.46% (136)	9% (144)
	Northern Ireland	5.81% (106)	3% (56)
	Missing data	0% (0)	0% (0)
Age (unweighted): Mean = 33.70 | Std. Dev. = 13.42| Range = 17-71 | Skewness = .57			
Age (weighted): Mean = 33.82 | Std. Dev. = 13.59| Range = 17-71 | Skewness = .56			

Table 5.1: Wave 6 sample characteristics, unweighted and weighted. Unweighted n = 1,824. Weighted n = 1,612. Details of whether a given variable is displayed in original format, or another as coded by the Researcher provided in column 1.

The weighting factor supplied with Understanding Society data lowers the overall number of respondents within the subsample from 1,824 to 1,612. It is assumed to provide a population more representative of the UK. More women are removed than men, meaning the gender ratio changes from around a 50:50 split, to 55:45 in favour of men. Gender is controlled for in analyses because it is a marker of inequality in employment outcomes, for example the ‘gender pay gap’ (Brynin, 2017). Similarly, educational attainment has a considerable bearing on employment outcomes, for example predicting wages better than any other factor in the UK (Howard *et al*, 2014; Naylor *et al*, 2015). Presently, highest educational attainment is reduced down to three categories for analysis; higher (university), further education (beyond age 16), and mandatory (minimum school leaving age). This recode eliminates a potential cohort effect from a change in the school leaving age in 1973 in England and Wales (Cowan *et al*, 2012) because those who left school at the earliest legal age are coded together in the mandatory category.

A greater prevalence of respondents of ethnic minority origin allows for the ethnicity control to be operationalised with a greater number of categories than was the case using OxIS data in Chapter 4, or in the following chapters based upon primary data. White British respondents are under-represented in unweighted data, and the weighting factor therefore boosts the proportion from 66% to 82%. Ethnicity is controlled for because it is also an established marker of inequality in employment outcomes – for example the ‘ethnicity pay gap’ (Longhi and Brynin, 2017) – and has been identified as a marker of differential SNS usage (Hargittai, 2008c). Urban density, in the form of a simplified urban/rural split, is controlled for due to the inclusion of first-level digital divide (Bimber, 2000) independent variables in some analyses – home access to a broadband connection, and ownership of a smartphone (access to mobile internet). In the UK at the time of the survey, rural broadband speeds were slower than in urban areas (Ofcom, 2018), and mobile internet coverage was more variable in less urbanised areas (Ofcom, 2018b). The proportion of rural-dwelling respondents is boosted marginally in the weighted sample.

The proportion of respondents with a disability – defined as a chronic impairment, health problem, or disability – is also boosted marginally by the weighting factor, from 28% to 31%. Disability is controlled for as it can act as another marker of disadvantage in employment outcomes, for example in full-time median hourly wages (‘The disability pay gap’; Longhi, 2017). Country of residence is included in some analyses to address the sampling discrepancy that occurs between primary and secondary analyses. The primary data sampling strategy targeted Scottish residents, whilst secondary analysis takes place at the UK level. Therefore interactions between being a Scottish resident and independent variables of interest are tested for geographical variation of effects. Marginal changes occur in the proportions of residents belonging to most UK countries in the unweighted sample.

Statistics for age are also shown in Table 5.1. The weighting factor has minimal impact on these. Age can be a differentiating factor in social capital, as younger people are more likely to make use of family connections rather than those formed themselves (Lin *et al*, 1981). Preliminary analyses identified a relatively strong and negative correlation between age and SNS use. Therefore age is viewed as an important control factor.

5.2.2 Dependent and independent variables

A consistent set of tests employing different outcomes surrounding employment form the analysis presented in this chapter. Dependent and independent variables are employed largely for a single analytical purpose, with the exception of three variables, which are operationalised as distinct independent variables for one set of tests, and as controls in other sets of tests. Frequencies of independent variables are documented in Table 5.2, grouped by analytical theme (analytical themes refer to groups of analyses, which are explained in further detail in 5.2.3).

Variable grouping (test code)	Independent variable description	Category	% Unweighted (freq.)	% Weighted (freq.): Rounded
Job-search techniques (Test B)	**Used social contacts in job search** (original)	Yes	54.33% (991)	57% (911)
		No	45.67% (833)	44% (701)
		Missing data	0% (0)	0% (0)
	Used internet in job search (original)	Yes	78.02% (1,423)	81% (1,301)
		No	21.98% (401)	19% (311)
		Missing data	0% (0)	0% (0)
	Used private recruitment agencies or Jobcentre in job search (original)	Yes	21.38% (390)	24% (382)
		No	78.62% (1,434)	76% (1,230)
		Missing data	0% (0)	0% (0)
Social network homogeneity (Test C)	**All friends have similar level of educational attainment to respondent** (recoded version operationalised in analysis)	Yes	26.97% (492)	30% (476)
		No	59.92% (1,093)	63% (1,023)
		Missing data	13.10% (239)	7% (113)
	All friends have similar level of income to respondent (recoded version operationalised in analysis)	Yes	7.73% (141)	8% (129)
		No	68.09% (1,242)	74% (1,200)
		Missing data	24.18% (441)	18% (283)
	All friends are employed (recoded version operationalised in analysis)	Yes	21.00% (383)	22% (348)
		No	68.20% (1,244)	74% (1,196)
		Missing data	10.80% (197)	4% (69)
	All friends live in the same area as respondent (recoded version operationalised in analysis)	Yes	12.12% (221)	14% (222)
		No	77.96% (1,422)	83% (1,335)
		Missing data	9.92% (181)	3% (55)

Table 5.2: Independent variables operationalised in analyses. Whether variable is operationalised in original format, or a recoded version is detailed in column 2. Job-search techniques are recorded in Waves 4 or 5, when the respondent was looking for work. Social network homogeneity is measured in Wave 6. Unweighted n = 1,824. Weighted n = 1,612.

The independent variables listed in Table 5.2 belong to two analytical sets. First there are three indicators of job-search activity, which refer to the period in Waves 4 and/or 5 when the respondent was recorded as looking for work. The three indicators denote whether a respondent searched online for jobs, enquired at private recruitment agencies or the Jobcentre, and asked a personal contact. The most commonly used technique in searching online. For clarification, the personal contact indicator does not differentiate between asking the contact through SNS or other means. Regression models that employ the job-search indicators as predictors of employment-based outcomes net of controls provide an assessment of whether particular job-search techniques have a significant impact on getting a job, or job quality.

Four indicators of social network homogeneity are employed in regression models under the same principles. These models are designed to test the effects of diversity in social networks on employment outcomes. Indicators of network homogeneity cover education levels, employment levels, income levels, and geographical dispersion. As binary indicators, they have been recoded from original, Likert scale format, to indicate a large amount of network homogeneity (e.g. ‘all my friends are employed’) versus other levels of homogeneity. The greatest occurrence of network homogeneity measured is educational attainment, at 30% of the weighted sample. The network homogeneity measures are derived from Wave 6 data, as the indicators are not present in Waves 4 or 5.

Table 5.3 provides details of measures employed as dependent variables in analyses. These all pertain to employment, fitting into two categories. The first dependent variable indicates whether respondents looking for work in Waves 4 or 5 were working in Wave 6, which is taken as a broad assessment of successful job search. Other dependent variables measure the quality of the job the respondents have in Wave 6, which reduce the sample universe to those who are employed.

Variable grouping	Dependent variable description	Category	% Unweighted (freq.)	% Weighted (freq.): Rounded
Job attainment	**Working in Wave 6** (derived)	Yes	51.26% (935)	54% (863)
		No	48.74% (889)	46% (749)
		Missing data	0% (0)	0% (0)
Job quality (if job attainment = 'yes')	**Job satisfaction** (recoded version operationalised in analysis)	Satisfied	68.56% (641)	73% (608)
		Not satisfied	20.64% (193)	23% (193)
		Missing data	10.80% (101)	4% (29)
	Pay satisfaction (recoded version operationalised in analysis)	Satisfied	45.03% (421)	49% (404)
		Not satisfied	44.60% (417)	48% (398)
		Missing data	10.37% (97)	3% (27)
	Job term: Employment mode (original)	Permanent	69.30% (648)	70% (545)
		temporary	26.63% (249)	23% (183)
		Missing data	4.06% (38)	7% (51)
	Net monthly pay (original, weighted)	Mean = 885 | Std. Dev. = 531| Range = 20-4,000 | Skewness = 1.34 | n = 710		
	Log of net monthly pay (derived, weighted)	Mean = 6.59 | Std. Dev. = .68| Range = 2.99-8.29 | Skewness = -.80 | n = 710		
	CAMSIS score (derived, weighted)	Mean = 48.67 | Std. Dev. = 11.97| Range = 28.16-84.94 | Skewness = .66 | n = 747		

Table 5.3: Dependent variables operationalised in analyses. Whether variable is operationalised in original format, or a derived version detailed in column 2. All data from Wave 6. Net monthly pay, log of net monthly pay, CAMSIS scores: unweighted statistics not listed.

Attainment of a job in Wave 6 includes both employees and people who are self-employed. Just over half of the sample were employed at the time of Wave 6 data collection. It should be noted that it is not assumed that the recorded job is a direct result of Wave 4 or 5 job searches, because respondents could have had several spells in-and-out of employment between Waves.

Job quality-related dependent variables operationalised are a mixture of self-assessments (job and pay satisfaction), and more objective measures. Although the veracity of self-assessments can be questioned (Kruger and Dunning, 1999), it is assumed that inclusion of more objective job quality measures results in a balanced overall analysis. Further, prioritising permanent over temporary employment as a measure of a successful job-search, as is done presently with the 'job term' variable, has received criticism with regards the US and UK employment markets for not indicating job security comprehensively (Kalleberg, 1996).

Table 5.4 details indicators operationalised both as independent and control variables. These are predictors of theoretical interest when modelling employment outcomes in their own right (for example the effect of SNS use on employment), and factors that should be controlled for in other analyses.

Variable description	Category	% Unweighted (freq.)	% Weighted (freq.): Rounded
SNS user (original)	Yes	68.53% (1,250)	76% (1,224)
	No	24.18% (441)	24% (387)
	Missing data	7.29% (133)	0% (1)
Has home broadband access (original; Household-level data)	Yes	86.51% (1,578)	85% (1,368)
	No	12.94% (236)	15% (237)
	Missing data	0.55% (10)	0% (7)
Owns a smartphone (original)	Yes	70.94% (1,294)	73% (1,173)
	No	22.04% (402)	25% (408)
	Missing data	7.02% (128)	2% (31)

Table 5.4: Variables operationalised as controls or independent variables. N = 1,824. Broadband access variable imported from household data file. All variables coded in original Understanding Society format.

Smartphone ownership is taken from Understanding Society Wave 5 if respondents were looking for work at the time of that survey, or Wave 6 otherwise. Home broadband access is a household-level variable. A majority of respondents own a smartphone, which typically give access to internet on the move, as well as a broadband connection at home. It should be noted, however, that 126 respondents do not have such home or mobile internet access (weighted sample), implying exclusion from internet access to at least some degree, otherwise known as the first-level digital divide (Robinson *et al*, 2003).

5.2.3 Analytical tests

Table 5.5 describes a structured series of tests that are applied within the context of each outcome listed in Table 5.3. The table also indicates research questions that are addressed by each test.

Test name	Independent variables	Modelling strategy	Research question(s) addressed
Test A	SNS user, Home broadband access, smartphone ownership	Used to predict each outcome net of each other and control variables	Research Question A1-3
Test B	Job-search methods (online, contacts, recruitment agency or Jobcentre)	Used to predict each outcome net of control variables.	Research Questions A1, A3
Test C	Network homogeneity (educational attainment, income level, geographical concentration, employment level)	Used to predict each outcome net of control variables	Research Questions A1, A2
Additional unreported test	Interaction of Scotland residence with independent variables in Tests A-C	Additional test based on each model constructed	

Table 5.5: Analytical structure details and research questions addressed.

Research questions are restated below in Table 5.6 for reference. Tests B and C follow the same modelling structure, whereby each measure of job-search method and network homogeneity is modelled separately predicting dependent variables, net of controls. Test A follows a slightly different structure, whereby independent variables are modelled together, net of controls, predicting each outcome. This is because of the inter-relatedness of the variables. For example, Not having or owning a smartphone would hinder SNS use, as mobile internet may not be an option.

The interaction of being a Scottish resident with each independent variable within models was also explored to test for any differential effects experienced in Scotland, given primary data was collected in that UK country. However results of these additional analyses are inconclusive and not reported, due to lack of case numbers within some interaction categories affecting the validity of results.

Research Question A: **Does SNS use benefit career management?**	Research Question B: **Who embraces the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	B1) Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	B2) Who uses the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	B3) Is there an uneven distribution of positive, career-outcome effects from weak tie social capital use?

Table 5.6: Thesis research Questions.

All analyses address Research Question A, or its sub-questions. Test A directly tests the effect of SNS use on employment outcomes (RQA), alongside testing for additional effects of broadband access and smartphone use, which effect autonomy of SNS use. Test B examines effects of accessing social capital through contacts (RQA1) and using the internet (RQA3) when job-seeking, alongside a measure that does not explicitly involve internet or social capital use (recruitment agencies or Jobcentre) as a control measure. Test C, through examining effects of social network composition on employment outcomes, addresses another dimension of the significance of social capital in the employment market (RQA1), and identification of effects of network diversity contribute to our understanding of the theorised benefits of weak ties (RQA2).

5.2.4 SNS use, home broadband access, smartphone ownership (Test A)

Analyses conducted within the previous chapter suggests that a divide amongst SNS users existed whereby a distinct SNS-user population enjoyed benefits such as better employment outcomes and wider benefits to human capital. This suggested that SNS use did provide a boost to career management, but only for certain people. This caveat reinforced literature review findings, in which internet users on the wrong side of the 'second-level digital divide' (Hargittai, 2008a) are not able to harness the potential capacity of SNS and the wider internet.

Test A extends this theme of analysis in context of a population actively seeking work.

DV = Employed in Wave 6		Model A.1.1 (Control)
Female		-.30*
Age		.00
Ethnicity	White other	-.70ᵻ
	Mixed	-.83*
	Asian	-.69**
	Black	-.14
	Other	-1.71*
Educational attainment	Degree	.76***
	FE	.06
Rural resident		.21
Disability		-.58***
Pseudo r2		.04
BIC		2139
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 5.7: Model A.1.1. Logistic regression predicting whether respondents looking for work in Waves 4 or 5 are in work in Wave 6. N = 1,399. Ethnicity reference category = White British. Educational attainment reference category = Mandatory education.

Table 5.7 shows results from a control model (A.1.1). Although the results do not directly address the Thesis' research questions, they do provide extra context in telling us a little more about the dependent variable. Results broadly reflect established patterns of employment stratification, for example in significant and negative effects for women and most ethnic minority groups (e.g. gender and ethnicity pay gaps; Brynin, 2017; Longhi and Brynin, 2017), and a significant boost for respondents with a degree-or-higher-level qualification (e.g. Naylor *et al*, 2015). Therefore as an indicator of job attainment, the dependent variable responds as expected. Table 5.8 details results from further models that include the controls described in Model A.1.1, in addition to the independent variables of key interest.

DV = Employed in Wave 6	Model A.1.2 (SNS use)	Model A.1.3 (smartphone ownership)	Model A.1.4 (home broadband access)
SNS user	.21	.02	.00
Smartphone ownership		.28ᵻ	.11
Broadband access			1.07***
Pseudo r2	.05	.05	.07
BIC	2144	2147	2113
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.8: Models A.1.2-A.1.4. Logistic regressions predicting whether respondents looking for work in Waves 4 or 5 are in work in Wave 6, net of controls listed in Model A.1.1. N = 1,399.

Model A.1.2 finds no significant effect on job attainment from SNS use. Models A.1.3-4 suggest a greater role for independent variables addressing internet access, rather than use. Smartphone ownership is suggested to have a positive effect of respondents being employed in Wave 6, and broadband access has a significant and positive impact, taking into account the other two factors.

A degree of collinearity was discovered between age and SNS use (.42 correlation within weighted sample) which potentially affected results in Models A.1.2-A.1.4. To control for this, further analyses splitting the sample by age was tried. Between 40 and 50 years of age was identified as a cut-off point whereby SNS use trends reversed from most respondents being users, to most not being users. Therefore Models A.1.2-A.1.4 were replicated amongst respondents aged 40 and under, and 50 and over. Neither replication found a difference in the effect of SNS use. This replication is carried out in context of all other dependent variables operationalised in Test A. Next, the process undertaken in Models A.1.1-4 was replicated in predicting the quality of employment that respondents had attained when questioned in Wave 6. Several indicators of employment quality were tested, beginning with job satisfaction. Control model results (Model A.2.1) are documented in Table 5.9. The sample universe is reduced to reflect analysis concerning only those who were employed in Wave 6.

DV = Satisfied with job		Model A.2.1 (Control)
Female		.76***
Age		.01
Ethnicity	White other	-.44
	Mixed	-.25
	Asian	.24
	Black	-.13
	Other	.14
Educational attainment	Degree	-.48*
	FE	-.11
Rural resident		-.34
Disability		-.33
Pseudo r2		.04
BIC		960
Key: ˈ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 5.9: Model A.2.1. Logistic regression predicting job satisfaction amongst respondents employed in Wave 6. N = 707. Ethnicity reference category = White British. Educational attainment reference category = Mandatory education.

Control model results predicting job satisfaction are markedly different compared to the control model predicting job attainment, and do not represent established trends concerning employment outcomes that are perhaps more typical (e.g. wages; Ericksen and Yansey, 1980). For example, a positive and significant boost to likelihood of being satisfied with Wave 6 jobs is discovered for women. The direction of this effect was reversed in Model A.1.1. Unexpected trends could be a reflection of the kind of jobs that are attainable. For example a job taken to exit unemployment may not be considered the respondent's ideal job. Table 5.10 lists results of Test A in predicting job satisfaction, net of controls.

DV = Satisfied with job	Model A.2.2 (SNS use)	Model A.2.3 (smartphone ownership)	Model A.2.4 (home broadband access)
SNS user	.31	.40	.38
Smartphone ownership		-.36	.40
Broadband access			.26
Pseudo r2	.04	.04	.04
BIC	965	969	975
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.10: Models A.2.2-A.2.4. Logistic regressions predicting respondent satisfaction with jobs in Wave 6, net of controls listed in Model A.2.1. N = 707.

Models A.2.2-4 find no significant impact of SNS use, smartphone ownership, and home broadband access in predicting job satisfaction. When these factors are introduced sequentially into the control model, model fit statistics also show that predictive power is not being enhanced.

DV = Satisfied with pay		Model A.3.1 (Control)
Female		-.28
Age		-.02*
Ethnicity	White other	-1.60*
	Mixed	-.62
	Asian	.07
	Black	-.61ᵻ
	Other	-.67
Educational attainment	Degree	.23
	FE	.54ᵻ
Rural resident		.24
Disability		-.84***
Pseudo r2		.06
BIC		1157
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 5.11: Model A.3.1. Logistic regression predicting pay satisfaction amongst respondents employed in Wave 6. N = 707.

Table 5.11 documents control model statistics predicting pay satisfaction. Results of control model A.3.1 differ quite distinctly from those of A.2.1. Several significant and negative effects are found – for age, a white other ethnic background, and for disability. A black ethnic background is suggested to have a negative effect, and education beyond compulsory but not to degree level is suggested to have a positive effect. Of significant effects, disability is an established marker of receipt of lower pay (Longhi, 2017).

DV = Satisfied with Pay	**Model A.3.2 (SNS use)**	**Model A.3.3 (smartphone ownership)**	**Model A.3.4 (home broadband access)**
SNS user	.06	.02	-.02
Smartphone ownership		.12	.07
Broadband access			.44
Pseudo r2	.06	.06	.06
BIC	1163	1169	1174
Key: ⁱ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.12: Models A.3.2-A.3.4. Logistic regressions predicting respondent satisfaction with pay in Wave 6 jobs, net of controls listed in Model A.3.1. N = 707.

In common with model series A.2 results, Models A.3.2-4 in Table 5.12 find no significant impact for SNS use, smartphone ownership, or home broadband access in predicting respondent satisfaction with pay. Based on Test A results, SNS use does not provide a boost to subjective job quality outcomes.

DV = Permanent employment		Model A.4.1 (Control)
Female		.59**
Age		-.01
Ethnicity	White other	-.84
	Mixed	-.67
	Asian	.05
	Black	-.32
	Other	-.14
Educational attainment	Degree	-.32
	FE	-.53ƚ
Rural resident		.07
Disability		-.42ƚ
Pseudo r2		.03
BIC		1022
Key: ƚ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 5.13: Model A.4.1. Logistic regression predicting permanent employment amongst respondents employed in Wave 6. N = 697. Ethnicity reference category = White British. Educational attainment reference category = Mandatory education.

Table 5.13 assesses job security. Permanent employment is predicted, as opposed to jobs that are temporary contract. Results show that few indicators are found to have a significant, or approaching significant, effect in predicting permanent employment arrangements. A particularly low pseudo r-square value for the model also suggests the factors in the control model do not explain variation in the dependent variable well. A significant boost in likelihood of being employed permanently for women is found. Table 5.14 shows results for Test A in the context of predicting permanent employment arrangements.

DV = Permanent employment	Model A.4.2 (SNS use)	Model A.4.3 (smartphone ownership)	Model A.4.4 (home broadband access)
SNS user	.17	.07	.07
Smartphone ownership		.36	.34
Broadband access			.10
Pseudo r2	.03	.03	.03
BIC	1027	1031	1037
Key: ˡ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.14: Models A.4.2-A.4.4. Logistic regressions predicting permanent employment amongst respondents employed in Wave 6, net of controls listed in Model A.4.1. N = 697.

SNS use, smartphone ownership, and home broadband access are not found to significantly influence job security. Further, BIC values increase from the control model when these factors are introduced, indicating no improvement in model fit.

Actual pay is tested next, through employment of both net monthly pay and log of net monthly pay indicators as dependent variables in Test A. Net monthly pay is transformed into a log to reduce the influence of positive outliers. Results of the two control models predicting each are listed together in Table 5.15.

DV = Net monthly pay (NMP); Log of net monthly pay (LNMP)		Model A.5.1 (Control; NMP)	Model A.6.1 (Control; LNMP)
Female		-247.91***	-.36***
Age		8.72***	.01***
Ethnicity	White other	-93.27	-.07
	Mixed	-38.24	.06
	Asian	6.22	-.01
	Black	-10.72	-.05
	Other	-75.19	.04
Educational attainment	Degree	272.45***	.29***
	FE	-61.38	-.19*
Rural resident		14.49	.04
Disability		-93.42ᵻ	-.13ᵻ
Constant		671.94***	6.43***
R-squared		.18	.18
BIC		9381	1257
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.15: Control models A.4.1 and A.5.1. Ordinary least squares regressions predicting net monthly pay and log of net monthly pay amongst respondents employed in Wave 6. N = 625.

Control model results predicting net monthly pay and log of net monthly yield similar results. A wage penalty for women, and bonuses for years of age and a degree-level or higher education occur as significant effects in both. Some divergence in results – a significant penalty for education beyond compulsory but not degree-level in Model A.6.1 – indicates outliers are having some effect in Model A.5.1. Table 5.16 details results from Test A in predicting both forms of net monthly pay.

DV = Net monthly pay (NMP); log of net monthly pay (LNMP)	Model A.5.2 (SNS use; NMP)	Model A.6.2 (SNS use; LNMP)	Model A.5.3 (smartphone ownership; NMP)	Model A.6.3 (smartphone ownership; LNMP)	Model A.5.4 (home broadband access; NMP)	Model A.6.4 (home broadband access; LNMP)
SNS user	22.92	-.02	32.88	.01	23.16	.01
Smartphone ownership			-45.82	-.13ᶧ	-57.10	-.13ᶧ
Broadband access					89.83	.04
Constant	643.40***	6.45***	677.43***	6.54***	611.30***	6.52***
R-squared	.18	.18	.18	.18	.18	.18
BIC	9588	1263	9593	1266	9598	1272

Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 5.16: Control models A.5.2-A.5.4 and A.6.2-A.6.4. Ordinary least squares regressions predicting net monthly pay and log of net monthly pay amongst respondents employed in Wave 6. Net of controls listed in Table 5.15. N = 625.

No significant effect of SNS use is found in either set of models predicting net monthly pay and log of net monthly pay respectively. Broadband access is not found to be associated with pay either. In Models A.5.3-4 results suggest that smartphone ownership may be associated on average with lower pay.

The last employment outcome subjected to Test A represents the social advantage of occupations. CAMSIS scores (male) combine occupational stratification with structures of social interaction to indicate level of access to social resources (Lambert, 2018). The higher an occupation scores (weighted sample range = 28-85), the higher the associated access to social resources. The incorporation of elements of social capital into this measure of job quality makes a compelling case for inclusion in present context. Control model results predicting CAMSIS scores are displayed in Table 5.17.

DV = Male CAMSIS scores		**Model A.7.1 (Control)**
Female		3.48***
Age		.06
Ethnicity	White other	-1.94
	Mixed	-8.00*
	Asian	1.12
	Black	-1.81
	Other	-2.48
Educational attainment	Degree	11.71***
	FE	6.75***
Rural resident		.47
Disability		-1.37
Constant		40.84***
R-squared		.23
BIC		5097

Table 5.17: Control model A.7.1. Ordinary least squares regression male CAMSIS scores amongst respondents employed in Wave 6. N = 663.

Results of the CAMSIS scores control model produce a mix of effects that are expected and unexpected, in relation to established employment market literature. Some further education produces a bonus to CAMSIS scores, and degree-level an additional bonus, which tally with expectations surrounding educational effects on employment outcomes (e.g. Hayward, Hunt and Lord; 2014). Whereas a significant bonus is also found for women, who are often cited as experiencing worse outcomes than men – for example the gender pay gap (Brynin,2017).

Table 5.18 shows results from the final iteration of Test A, employing SNS use, broadband access, and smartphone ownership indicators to predict CAMSIS scores.

DV = Satisfied with Pay	Model A.7.2 (SNS use)	Model A.7.3 (smartphone ownership)	Model A.7.4 (home broadband access)
SNS user	3.00*	2.30ᶧ	2.27ᶧ
Smartphone ownership		2.47ᶧ	2.41ᶧ
Broadband access			.40
Constant	37.14***	35.44***	35.14***
R-squared	.24	.24	.24
BIC	5096	5098	5104
Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 5.18: Models A.7.2-A.7.4. Ordinary least squares regressions predicting CAMSIS scores of Wave 6 jobs, net of controls listed in Model A.6.1. N = 663.

SNS use is found to have a significant and positive effect on CAMSIS scores in model A.6.2. When smartphone ownership and home broadband access are introduced in Models A.6.3 and A.6.4 the variable falls below the 5% set threshold for statistical significance. Introduction of SNS use to the original control model (A.6.1) also improves model fit, evidenced through a slight decrease in the BIC statistic. Smartphone ownership also falls just short of the statistical significance threshold in those models. Tentative support for a positive link between SNS use and career outcomes is therefore found. This impact appears to be mediated somewhat by smartphone ownership – a factor more associated with the first-level digital divide (autonomy of use), than the second-level digital divide. Home broadband access – another variable more associated with the first-level digital divide – has no impact on CAMSIS scores.

Results from Models A.7.2-4 suggest that a positive impact from SNS use may be being produced, net of broadband access at home at smartphone ownership, although this cannot be confirmed on current evidence. Findings reinforcing the concept of SNS as a career management tool to more easily manage and access social capital are not delivered by other models operationalising a range of employment outcome variables. Overall Test A results suggest that SNS use is not impacting career management in the way that authors such as Rainie and Wellman (2012) envisage. Similarly, although this Thesis does not place particular emphasis on first-level digital divide factors with regards consequences for career management, it should be noted that at aggregate level, these analyses suggest no impact on job quality. Broadband access at home is however found to positively influence job attainment, although results do not suggest a role for social capital in getting a job.

5.2.5 Job-search techniques

This section presents and analyses results from Test B. The employment outcomes operationalised in Test A are each modelled to explore impacts of different methods of job-searching when respondents were looking for jobs in Waves 4 or 5. Three types of job-search are employed as independent variables in these models. Searching online for jobs represents productive internet use, and therefore is associated with the theme of the second-level digital divide (Hargittai, 2008a). Asking a contact is the second form of job-search technique, and is intended to represent social capital expenditure. Use of SNS to engage contacts in the job-search cannot be separated from other channels, but is controlled for in the models, which enables such a separation to an extent. The final job-search measure denotes use of private recruitment agencies and/or the Jobcentre, and is intended as a comparison in models to online searches and use of contacts. Use of recruitment agencies/Jobcentre is not intended to represent a method or factor of particular interest in job seeking.

Control models predicting each outcome are produced in addition to Test A control models documented in chapter section 5.2.4. These have been produced to account for slight variations in sample universes as a result of inclusion of different independent variables in the models. However because the differences are not substantial, it is not worthwhile to report control variable effects within test B control models in this section.

The first iteration of Test B measures for impact of the different job-search techniques on job attainment. The dependent variable representing getting a job simply denotes that respondents who were unemployed and looking for work in Waves 4 or 5 were employed at the time of Wave 6 data collection. In common with all iterations of Test B, each job-search technique is modelled separately in predicting job attainment to test for effects in isolation of other techniques, then modelled together.

DV = Employed in Wave 6	**Model B.1.1 (control)**	**Model B.1.2 (contact use)**	**Model B.1.3 (online search)**	**Model B.1.4 (recruitment agencies and/or Jobcentre)**	**Model B.1.5 (all job-search techniques)**
Contact use		.33*			.36**
Online search			.18		.14
Recruitment agency/Jobcentre				-.24	-.35*
Pseudo r2	.06	.07	.06	.07	.07
BIC	2091	2089	2097	2095	2096
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.19: Models B.1.1-B.1.5. Logistic regressions predicting employment in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 1,399.

Table 5.19 shows firstly a significant and positive effect on job attainment when contact use is modelled to predict the dependent variable in isolation from other independent variables (hereafter referred to as 'modelled separately'). An improvement in model fit via a BIC statistic decrease also shows contact use inclusion helps to explain variance in the dependent variable. Online search and use of recruitment agencies and/or the Jobcentre (hereafter referred to as 'use of agencies') are not found to significantly effect job attainment when modelled separately, and worsen model fit. When modelled together in B.1.5, contact use increases in statistical significance showing broadly the same effect, and a negative effect of use of agencies becomes significant. Online search is not found to have a significant effect net of other search techniques. Results suggest that social capital expenditure helps in getting a job, and that in context of a broader range of strategies, some can have a negative effect on job attainment.

Tables 5.20-5.21 detail results on the quality of jobs of employed respondents in Wave 6.

DV = Satisfied with job	**Model B.2.1 (control)**	**Model B.2.2 (contact use)**	**Model B.2.3 (online search)**	**Model B.2.4 (recruitment agencies and/or Jobcentre)**	**Model B.2.5 (all job-search techniques)**
Contact use		.27			.30
Online search			.01		-.10
Recruitment agency/Jobcentre				.04	.05
Pseudo r2	.04	.04	.04	.04	.05
BIC	950	954	956	956	924
Key: ' p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.20: Models B.2.1-B.2.5. Logistic regressions predicting job satisfaction of respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 701.

Measured job-search techniques are not found to significantly influence job satisfaction (Table 5.20). Individually, the techniques worsen model fit through increased BIC values, although when modelled together, model fit does improve.

DV = Satisfied with pay	Model B.3.1 (control)	Model B.3.2 (contact use)	Model B.3.3 (online search)	Model B.3.4 (recruitment agencies and/or Jobcentre)	Model B.3.5 (all job-search techniques)
Contact use		.03			-.04
Online search			.31		.30
Recruitment agency/Jobcentre				.16	.12
Pseudo r2	.06	.06	.06	.06	.06
BIC	1154	1161	1158	1160	1171
Key: ᑊ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.21: Models B.3.1-B.3.5. Logistic regressions predicting pay satisfaction of respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 707.

Table 5.21 details results of Test B conducted in the context of predicting pay satisfaction. The test finds no influence of job-search technique on pay satisfaction. Model fit statistics worsen in each additional iteration from the control model, further suggesting that techniques undertaken do not influence how satisfied respondents are with pay in their Wave6 jobs.

DV = Permanent employment	Model B.4.1 (control)	Model B.4.2 (contact use)	Model B.4.3 (online search)	Model B.4.4 (recruitment agencies and/or Jobcentre)	Model B.4.5 (all job-search techniques)
Contact use		.21			.07
Online search			.69**		.65*
Recruitment agency/Jobcentre				.22	.11
Pseudo r2	.03	.03	.04	.03	.04
BIC	1014	1019	1009	1020	1022
Key: ᑊ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.22: Models B.4.1-B.4.5. Logistic regressions predicting permanent employment arrangements for respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 697.

Table 5.22 looks at whether the respondent in employment in Wave 6 is in permanent employment. Contact use and use of agencies are not found to significantly influence job security. Online job searches however are found to have a significant effect, both when modelled separately and together with the other search techniques. Online search only (B.4.3) is the only iteration of Model B.4 that improves model fit through a BIC statistic increase. Therefore, results of this Test B iteration suggest that jobs found online are more likely to be permanent employment than those who did not.

DV = Net monthly pay	**Model B.5.1 (control)**	**Model B.5.2 (contact use)**	**Model B.5.3 (online search)**	**Model B.5.4 (recruitment agencies and/or Jobcentre)**	**Model B.5.5 (all job-search techniques)**
Contact use		44.39			17.27
Online search			102.84*		80.80
Recruitment agency/Jobcentre				120.13*	107.54ᵻ
Constant	880.09***	847.34***	790.19***	835.54***	761.21***
R-squared	.18	.18	.18	.19	.19
BIC	9573	9604	9601	9598	9609

DV = Log of net monthly pay	**Model B.6.1** (control)	**Model B.6.2** (contact use)	**Model B.6.3** (online search)	**Model B.6.4** (recruitment agencies and/or Jobcentre)	**Model B.6.5** (all job-search techniques)
Contact use		.04			.01
Online search			.12		.10
Recruitment agency/Jobcentre				.12ᵻ	.11
Constant	6.82***	6.79***	6.72***	6.77***	6.69***
R-squared	.18	.18	.19	.19	.19
BIC	1247	1278	1276	1275	1285

Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 5.23: Models B.5.1-B.5.5 and B.6.1-B.6.5. Ordinal least squares regressions predicting net monthly pay and log of net monthly pay respectively for respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 625.

Table 5.23 shows that operationalisations of net monthly pay deliver varying results. In natural form, online job searches and use of agencies are both found to significantly boost pay when modelled separately. These significant effects however diminish when all searches are modelled together. Social capital expenditure, proxied through contact use, is not found to have a significant bearing on pay in any iteration of Model B.5. In Model B.6, when outliers are controlled for, no search technique is found to significantly influence pay. Use of agencies approaches significance in Model B.6.4. Aggregate results from the two sets of models therefore suggests that when monthly pay if operationalised in a realistic fashion, use of different forms job-search techniques do not impact this measure of job quality in context of respondent jobs in Wave 6.

The final results reported for Test B operationalise male CAMSIS scores as dependent variable. Results are reported in Table 5.24.

DV = Male CAMSIS scores	**Model B.7.1 (control)**	**Model B.7.2 (contact use)**	**Model B.7.3 (online search)**	**Model B.7.4 (recruitment agencies and/or Jobcentre)**	**Model B.7.5 (all job-search techniques)**
Contact use		-1.61			-1.90ᶧ
Online search			1.30		2.05
Recruitment agency/Jobcentre				-.93	-.86
Constant	46.71***	47.40***	45.43***	46.84***	46.18***
R-squared	.24	.25	.24	.24	.25
BIC	5082	5107	5110	5110	5117
Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.24: Models B.7.1-B.7.5. Ordinal least squares regressions predicting male CAMSIS scores of respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 663.

Models predicting CAMSIS scores find no effect for job-search techniques. When techniques are modelled together, contact use is suggested to result in a penalty on CAMSIS scores, but falls short of statistical significance. Further, no model improves the model fit of the control (B.7.1).

In summary, use of social capital in enquiring with a contact about jobs resulted in respondents being more likely to be employed in Wave 6. Use of agencies when job seeking in Waves 4 or 5 made Wave 6 employment less likely. Job quality in Wave 6 was largely not associated with types of job-search carried out in Waves 4 and 5, although searching online was found to increase likelihood of having a permanent employment arrangement.

Given the caveat of doubt over effectiveness of this proxy outcome in representing job quality, and lack of effects on other job quality outcomes, it must be concluded that while use of social capital seems to help in securing employment, it does not affect the quality of the job secured. Use of the internet in job-seeking aspects of career management does not affect attainment or quality of jobs.

5.2.6 Network Homogeneity

This final results section presents and scrutinises analyses conducted as part of Test C, exploring the role that the character of social networks has on career management. Homophily is a powerful social force. The tendency of individuals to cluster together on the basis of shared characteristics can reinforce employment market inequalities (McPherson *et al*, 2001). The concept of weak ties (Granovetter, 1974) implies diversity of characteristics to some extent in networks, as strong ties are more likely to be homophilous. Indicators of network diversity, or lack of, employed in Test C address the theme of social capital influence in career management, and extend the concept of weak ties.

Four indicators of network homophily (lack of diversity) are employed as independent variables predicting the employment outcomes featured in Tests A and B. The binary indicators represent responses indicating that all respondent friends are similar to them, versus other responses. Themes covered by the four indicators are level of education, employment level (all friends employed, regardless of respondent status), geographical area (all friends live close by), and income. Independent variables are modelled separately from each other in predicting the dependent variables, as effects net of each other are not of interest. A factor analysis of the four indicators finds that they do not load on to one single factor. Therefore the homophily measures do not all measure a single concept of homophily, rather different aspects of it.

As was the case in reporting Test B results, bespoke control models predicting each dependent variable are constructed. However these are not reported in detail due to similarities with control models reported with Test A results.

DV = Employment in Wave 6	Model C.1.1 (control)	Model C.1.2 (all friends similar level of education)	Model C.1.3 (all friends earn similar)	Model C.1.4 (all friends employed)	Model C.1.5 (all friends live in same geographical area as resp.)
Independent variable		-.13	-.39	.78***	.40ᵻ
Pseudo r2	.07	.07	.07	.09	.07
BIC	1697	1703	1700	1676	1699
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.25: Models C.1.1-C.1.5. Logistic regressions predicting employment in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 1,128.

Table 5.25 details results of the homophily measures predicting job attainment in Wave 6 of respondents looking for work in Waves 4 or 5. Model C.1.4 finds a significant and positive effect of employment level homophily on job attainment, and the model improves on the model fit of the control (C.1.1). Other homophily measures are not found to have a significant effect on job attainment, although the estimation for geographical homphily (C.1.5) is approaching significance. Regarding the significant effect, analyses suggest that high levels of employment in personal networks result in a greater chance of getting a job. Other measures of homophily are not found to make a difference. The significant effect identified is harmonious with findings from similar analyses of Understanding Society data (Cappellari and Tatsiramos, 2011; 2015). It seems logical that having high levels of unemployment amongst friends is associated with increased likelihood of unemployment exit for reasons other than friends in jobs being more likely to hear about other job vacancies and passing that information on. For example, high levels of employment in social groups is likely reflective of expectations. Employment as a concept is likely normalised.

Further dependent variables operationalised in Test C measure job quality. Table 5.26's results pertain to job satisfaction amongst respondent employed in Wave 6.

DV = Satisfied with job	Model C.2.1 (control)	Model C.2.2 (all friends similar level of education)	Model C.2.3 (all friends earn similar)	Model C.2.4 (all friends employed)	Model C.2.5 (all friends live in same geographical area as resp.)
Independent variable		-.04	.67	.34	-.32
Pseudo r2	.05	.05	.05	.05	.05
BIC	790	796	793	794	795
Key: ˈ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.26: Models C.2.1-C.2.5. Logistic regressions predicting job satisfaction amongst respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 582.

Model series C.2 results show no significant impact of social network homophily on job satisfaction. Model fit values do not improve on the control model in each iteration.

DV = Satisfied with pay	Model C.3.1 (control)	Model C.3.2 (all friends similar level of education)	Model C.3.3 (all friends earn similar)	Model C.3.4 (all friends employed)	Model C.3.5 (all friends live in same geographical area as resp.)
Independent variable		.25	.42	-.24	-.26
Pseudo r2	.07	.07	.07	.07	.07
BIC	991	995	995	995	996
Key: ˈ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.27: Models C.3.1-C.3.5. Logistic regressions predicting pay satisfaction amongst respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 590.

Table 5.27 lists results of the next iteration of Test C, predicting satisfaction with pay of respondents employed in Wave 6. Results of Test C.3 predicting pay satisfaction mirror those predicting job satisfaction amongst respondents employed in Wave 6. Addition of homophily indicators does not improve model fit in relation to the controls, and no significant effects are found amongst independent variables.

DV = Permanent employment arrangement	Model C.4.1 (control)	Model C.4.2 (all friends similar level of education)	Model C.4.3 (all friends earn similar)	Model C.4.4 (all friends employed)	Model C.4.5 (all friends live in same geographical area as resp.)
Independent variable		.04	.95*	.60*	.20
Pseudo r2	.04	.04	.05	.05	.04
BIC	854	860	854	851	859
Key: ˈ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.28: Models C.4.1-C.4.5. Logistic regressions predicting permanent employment arrangements amongst respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 578.

Table 5.28 describes results of models employing social network homophily indicators to predict permanent employment arrangements, as opposed to temporary in some way. Model C4 iterations find significant effects of some aspects of social network homophily in impacting this measure of job security. For respondents who have high levels of homophily amongst their friends in context of income and employment levels, they are found to have a greater likelihood to be in more stable employment. Model C.4.4 improves model fit from the control (C.4.1).

DV = Net monthly pay	**Model C.5.1 (control)**	**Model C.5.2 (all friends similar level of education)**	**Model C.5.3 (all friends earn similar)**	**Model C.5.4 (all friends employed)**	**Model C.5.5 (all friends live in same geographical area as resp.)**
Independent variable		-93.37*	4.60	122.13*	-167.15**
Constant	817.47***	858.08***	817.26***	800.65***	871.39***
R-squared	.18	.19	.18	.19	.20
BIC	8085	8088	8091	8085	8084
DV = Log of net monthly pay	**Model C.6.1** (control)	**Model C.6.2** (all friends similar level of education)	**Model C.6.3** (all friends earn similar)	**Model C.6.4** (all friends employed)	**Model C.6.5** (all friends live in same geographical area as resp.)
Independent variable		-.13*	.03	.17**	-.21**
Constant	6.70***	6.76***	6.70***	6.68***	6.77***
R-squared	.19	.20	.19	.20	.20
BIC	1076	1077	1082	1074	1074
Key: ' p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.29: Models C.5.1-C.5.5 and C.6.1-C.6.5. Ordinal least squares regressions predicting net monthly pay and log of net monthly pay respectively for respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 525.

Table 5.29 shows that the two different operationalisations of net monthly pay produce similar findings when modelled in Test C. Homophily in social networks through the proxies of education level, employment level, and geographical area are all found to significantly effect pay levels of employed respondents. Income homophily is found to not have a significant impact. Of the significant effects, respondents whose friends all have a similar level of education to them is associated with lower monthly wages, as are those whose friends are all concentrated in the same area that they live. Respondents whose friends are also all employed receive a boost to monthly pay. Model iterations that operationalise employment level and geographical area homophily broadly improve model fit from the controls. Iterations testing impacts of income and education level homophily on pay worsen model fit.

DV = Male CAMSIS scores	Model C.7.1 (control)	Model C.7.2 (all friends similar level of education)	Model C.7.3 (all friends earn similar)	Model C.7.4 (all friends employed)	Model C.7.5 (all friends live in same geographical area as resp.)
Independent variable		-2.09ᵻ	-1.09	2.35*	-3.25*
Constant	46.20***	47.13***	46.31***	45.89***	47.25***
R-squared	.23	.23	.23	.24	.24
BIC	4244	4246	4250	4245	4244
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Table 5.30: Models C.7.1-C.7.5. Ordinal least squares regressions predicting male CAMSIS scores of respondents employed in Wave 6, net of controls operationalised in Test A, and SNS use, smartphone ownership, home broadband access. N = 548.

Table 5.30 shows effects of network homophily on CAMSIS scores broadly similar to effects on net monthly pay. Although no significant effect of educational network homophily is found, it is approaching significance. Income homophily is not found to have a significant effect, and network homophily in employment levels and geographical area significantly impact CAMSIS scores. Respondents whose friends are also all employed receive have higher CAMSIS scores, and those whose friends all live in the same area as them have lower scores. Only one iteration of model series C.7 improves model fit from the control (C.7.1) – geographical network homophily, for which the BIC score remains the same, but the r-squared value improves.

Analyses presented in this section tested for effects of social network characteristics on both job attainment and job quality amongst respondents who were previously active in their job search. At the aggregate level, network effects are prevalent, net of demographic, internet access, and SNS use measures. This general trend suggests the influence of social relations in career management is based largely upon strong ties. Although respondents may be referring to some acquaintances, or friends they are not particularly close to, in some answers, close friends (strong ties) will clearly be taken into account in response to the questions respondents are asked regarding the make-up of personal networks. Relating to social influence on career management, directionality of relationships is not established within the scope of analyses. Lack of diversity in networks could be the result of homophily (McPherson *et al*, 2001). Equally, lack of diversity could be explained by the diffusion of characteristics amongst existing relations (Christakis and Fowler, 2009).

Network homophily when all friends are employed is found to have a positive effect on respondent's likelihood of being in employment. For those in employment at the time of Wave 6 data collection, the same type of network homophily is positively associated with three of the five measures of job quality operationalised (permanent employment, net monthly pay, and CAMSIS scores). However, job and pay satisfaction were not found to be influenced by any measures of network homophily, nor with any of the independent variables assessed in Tests A and B. Given the subjective nature of these measurements, this perhaps highlights idiosyncrasies in subjective assessments. By contrast multiple measured factors across the tests were significantly associated with net monthly pay, which is a more objective assessment of financial recompense in employment.

Network homophily measured via income levels (all friends earning roughly the same income as respondent) was not found to be linked with job quality, other than having a positive influence on respondent likelihood of being in permanent employment. Network homophily measured via geographical area (all friends live in same area as respondent) is found to negatively influence two measures of job quality – CAMSIS scores and pay levels. Finally homophily measured via education levels (all friends have similar level of educational attainment), is negatively associated with pay levels.

In addressing the question of how network diversity affects career management, results vary. Three instances of diversity having a positive link to job quality are found (geographical on CAMSIS scores and net monthly pay, and education levels on pay). Four instances of diversity negatively affecting job quality are identified to balance positive effects out (income and employment levels on likelihood of permanent employment, and employment levels on net monthly pay and CAMSIS scores). Of the measures of network diversity that are consistently identified as linking to job quality, it seems to be that geographical diversity appears to be a good thing for job quality, but employment level diversity amongst friends is associated with worse job quality. The latter pattern might reflect that unemployment amongst contacts is a negative social capital in many circumstances. In relation to job attainment, the same effect of social network employment levels is identified. High levels of employment amongst friends means the respondent is more likely to exit unemployment.

5.3 Conclusion

SNS use is suggested to have little impact on career-based outcomes through results presented within this chapter. The role of social capital in both job attainment and quality of attained jobs is also probed extensively, and on the surface produces few strong associations. This too suggests little influence of composition of social networks in both job attainment and quality of jobs attained amongst this sample of job seekers.

First, Test A examined the role of first-and-second level digital divide (Hargittai, 2008a) factors in relation to employment outcomes. SNS use, as well as being a point of second-level digital divide reference (whether people use SNS who have good internet access), is asserted to enable users to cultivate advantageous social connections in context of career management (Rainie and Wellman, 2012). Second-level digital divide literature suggests that elements of the online population do not have the necessary skill required to take such advantage of SNS (Hargittai and Hsieh, 2010). Chapter 4 identified these processes amongst a sample of internet users. SNS use was found to predict attainment of jobs advertised online, which in turn were of relatively high quality. Further, those SNS users more likely to get online jobs were also more likely to productively utilise wider internet space in a career management context. This population was identified as distinctly different from the general population of internet and SNS users, identifying the existence of second-level digital divides amongst respondents. Results presented in this chapter find no boost to job attainment or quality through SNS use. Amongst first-level digital divide factors tested, home broadband access is found to boost respondents' likelihood of job attainment, but not quality. Smartphone usage however is not found to significantly affect either. With reference to digital divides then, some evidence supports a role for the first-level digital divide in career management, but this chapter finds no evidence of a second-level digital divide effect. Although second-level digital divide scholars such as Hargittai (2008) proposed a shift in scholarly focus towards inequalities amongst internet users due to mass internet connectivity in western society, present analysis suggests a continued role for the first-level divide.

Although no significant role is found relating to SNS use in career management, suggesting social capital does not have an instrumental role in job attainment or quality, other results presented within this chapter provided conflicting evidence. Test B measured the effect of modes of job searches when respondents were seeking work in Waves 4 or 5, in context of Wave 6 employment outcomes. Results showed increased likelihood of job attainment when social capital is used, although no effect on quality of the attained job was found. In contrast to Chapter 4 conclusions, online job searches had no effect on later employment outcomes.

Social capital was found to be influential in career management also in Test C results. In testing the effect of network homophily/diversity through proxies of similarities in employment levels, income levels, educational attainment and geographical dispersion of friends, significant effects were found for both job attainment and quality. High levels of employment in friend networks improved the chances of respondents later becoming employed, and having better job quality (via the majority of job quality metrics employed). Low geographical dispersion of friends – i.e. all respondent friends resident in same area as respondent – were linked to lower levels of job quality amongst those who were employed in Wave 6 (although did not effect attainment of these jobs).

In relation to indicators of job quality, analyses suggested that the most subjective measures – job and pay satisfaction – do not perform well as employment outcomes. Variation in whether respondents are satisfied or not was difficult to predict, and pay satisfaction results did not mirror results from models operationalising a more objective measurement of recompense for employment (net monthly pay).

In summary, it seems relatively clear that characteristics of social networks can effect career management, and that social capital expenditure can aid job acquisition, however, no evidence is found that such processes proxy through SNS use. This could be because of variation in outcomes stemming from SNS use, rather than lack of SNS utility in career management. The next chapters turn to analyses of bespoke data in specific contexts where the career benefits of SNS might be particularly distinct and may reveal patterns that did not emerge from the broader national data represented by the Understanding Society survey.

Chapter 6 – Further Education student data analysis

6.1 Introduction

This chapter presents results from analyses of primary data collected from further education (FE) students studying at Scottish colleges (for further information relating to data collection, see 3.4.1 'Further education student survey'). Following on from identification of an online population of SNS users that used the internet productively and experienced preferential employment outcomes that was different to the general SNS-using population in Chapter 4, present analyses stem from this precedent. Outcomes associated both with categories of information relevant to career management gained from SNS contacts and types of ties that such information was received from are interrogated to provide a contribution that secondary data, as the focus of Chapters 4 and 5, did not allow for.

6.1.1 Literature overview

Social capital, a distinct form of capital that interacts with the other forms of capital (Bourdieu, 1986). Through the lens of employment outcomes, it is a component of human capital. When developed and nourished, information received through contacts can be critical to gaining new positions (Granovetter, 1973; Lin, 1999). Possession of strategic connections leads to positive performance evaluations and greater compensation (Burt, 2004). Strategic connections are likely composed of weak ties, based on the principle of homophily (McPherson *et al*, 2001). The relative value of weak ties depends on place within the wider structure, as strong ties of privileged individuals are likely valuable too (Lin and Dumin, 1986).

In the networked age SNS represent a tool that individuals can use to circumvent traditional barriers prohibitive to the development of a network of weak ties. With application, these ties can provide invaluable information for the advancement of careers (Rainie and Wellman, 2012). Research linking social capital use via SNS to employment outcomes finds mixed evidence regarding usefulness for cultivation of bridging social capital (Shpigalman and Gill, 2014) and in employment outcomes linked to weak tie use in the job-search process (Gee *et al*, 2017). Research into internet use and outcomes amongst the online population identifies traditional, structural barriers towards productive internet use (the 'second-level digital divide' (Hargittai, 2008a)) that mark experience of offline inequality.

6.1.2 Research questions addressed

A description of analytical themes and the research questions that each addresses are provided in this sub-section for reference. Table 6.1 restates Thesis research questions outlined in 2.8.2.

Research Question A: Does SNS use benefit career management?	**Research Question B: Who embraces the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	**B1)** Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	**B2)** Who uses the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	**B3)** Is there an uneven distribution of positive, career-outcome effects from weak tie social capital use?

Table 6.1: Thesis research questions.

Table 6.2 details how three analytical themes in context of career management are assessed in this chapter: informational SNS use; the strength of weak ties; and productive internet use. Grouped into these themes, topics of individual analysis are detailed in relation to the research question that they address. A summary of the way indicators of these questions are operationalised in the analytical models is also included.

Analytical theme	**Analysis question**	**Modelling strategy**	**Research question(s) addressed**
A: Informational SNS use	**(A1)** Does SNS use provide a career management boost?	2 models: Receipt of information from an SNS contact predicting career optimism	Research Question A1-3
	(A2) Does social capital use help career management?	2 models: Receipt of information from a contact (not via SNS) predicting career optimism	Research Questions A1, A3
	(A3) Does online skill level effect receipt of information through SNS?	2 models: Self-rated online skill level predicting receipt of two forms of information through SNS	Research Question B1
B: Productive internet use	**(B1)** What personal characteristics effect online skill?	1 model: High level of online skill predicted by personal characteristics (control variables)	Research Question B2
	(B2) Does a high level of online skill predict other	3 models: High level of online skill predicting 3 proxies of productive internet use	Research Question B2

	productive uses of the internet?		
	(B3) Are productive internet uses predictive of receipt of career-related SNS information?	6 models: 3 proxies of productive internet use predicting receipt of 2 forms of career-related information via SNS	Research Questions A1, A3
C: The strength of weak ties in career management	**(C1)** Are weak tie career information resources associated with better employment outcomes?	1 model: Naming of 1 weak tie or more within top 3 career information contacts predicting career optimism	Research Question A2 (in conjunction with analysis C2)
	(C2) Are respondents with more valuable weak tie resources more likely to receive career-related information via SNS?	2 models: Naming of 1 weak tie or more within top 3 career information contacts predicting receipt of 2 forms of career information via SNS	Research Question A2 (following from Analysis C1)

Table 6.2: Analytical structure details and research questions addressed.

6.2 Sample characteristics

The sample consists of 347 respondents who were either in their last 6 months of studying an FE course at a Scottish college (82%), or were within 6 months of having finished a course (18%) at the time of data collection. Such parameters were set to disqualify respondents less likely to be actively thinking about the next step in their career. Respondents studied their courses at a range of institutions. 19 are represented. All results presented within this chapter are produced by unweighted analyses. Therefore, sample characteristics are especially important, given the absence of tools to mitigate sample biases. The demographic characteristics presented in this section serve two functions within multivariate analyses. First, they are operationalised as controls in regression models to reduce identification of spurious relationships between independent and dependent variables. Second, demographics act as independent variables in analyses exploring differentiated uses and outcomes associated with SNS and internet use, and employment outcomes. Understanding sample properties provides context for results of these multivariate analyses. Table 6.3 presents demographic distributions and gives information on how these characteristics are operationalised in analyses.

Variable description (coding detail if different in analyses)	Category	% of sample (freq.)	% of valid sample (if some data missing)
Gender	Male	44.67% (155)	44.93%
	Female	54.76% (190)	55.07%
	Missing data	0.58% (2)	
Highest educational attainment (dummy binary variables in analyses)	High (SCQF 8-12)	24.50% (85)	24.64%
	Medium (SCQF 6-7)	50.14% (174)	50.43%
	Low (SCQF 1-5)	24.50% (86)	24.93%
	Missing data	0.58% (2)	
Ethnicity (binary 0 'White UK', 1 'Other' in analyses)	White UK	89.05% (309)	
	White other	7.49% (26)	
	Asian	2.02% (7)	
	Black	0.29% (1)	
	Mixed race	1.15% (4)	
	Missing data	0% (0)	
Parent with a degree (inherited social advantage)	Yes	31.99% (111)	
	No	68.01% (236)	
Language spoken at home	English	92.80% (322)	
	Other	7.20% (25)	
Urban density	Urban	51.59% (179)	52.34%
	Rural	46.97% (163)	47.66%
	Missing data	1.44% (5)	
Age: Mean = 25.33 | Std. Dev. = 9.40 | Range = 16-58 | Skewness = 1.37 Missing = 0.86% (3)			

Table 6.3: Demographic characteristics of respondents. Alternative operationalisation of data in analyses indicated in column 1. N = 347.

47% of respondents reside in rural areas, as defined in the survey instrument as 'small town/village' (Appendix 1a, question 15). Although a relatively crude measurement of urbanisation level, it closely relates to the Scottish Government's definition of rural areas, which is settlements with a population of less than 3,000. This definition comprises 17% of Scotland's population (Scottish Government, 2018), indicating that rural residents are over-sampled presently. A lack of additional information on urban or rural categorisation given in the survey instrument likely affected respondent selection, and this was addressed in subsequent surveys. Urban density is included in analyses due slower broadband speeds in UK rural areas (Ofcom, 2018b), that could inhibit productive internet use.

The sample is fairly evenly split by sex, a slightly majority of valid responses being female (55%). Sex is an important marker of uneven employment-based outcomes such as the gender pay gap (Brynin, 2017), and for women utilisation of social capital in career management (e.g. Lutter, 2015).

Educational attainment is measured using the Scottish Credit and Qualifications Framework (SCQF), which combines academic and vocational qualifications on a scale of 1 (lowest) to 12 (highest) (SCQF, N. D.). To operationalise appropriately for analysis this scale is reduced to three categories of low, medium and high. This reduction entailed grouping 1-5 on the SCQF scale into the low category, 6-7 medium, and 8-12 high. The reduction ensured meaningful categories (for example 'high' represents higher education), whilst deleting outlier scale categories such as 12 (doctorate) and 1 (National 1) because they contained a very small number of, or no respondents. Given a majority of respondents were still undergoing formal education at the time of data collection, current attainments interact somewhat with age. As a result, representativeness is not possible to assess. Education level is the best predictor of UK employment outcomes (e.g. Howard *et al*, 2014) and is identified as a marker of differential internet uses in second-level digital divide literature (Wei and Hindman, 2011).

Statistics relating to the age distribution of the sample show, as would likely be expected for a college student population, a young population. The average age is 25 years old, and skewness of 1.37 denotes a population that is not normally distributed. Implications to consider in interpretation of results are a cohort effect with regards proficiency in utilising technology and the internet – theoretically this population should be more skilled than the general population (Prensky, 2001) – and the difficulty in assessing career outcomes amongst this population. Some respondents may not have worked before, and amongst those who have, many instances may be non-career related work to contribute towards living costs. The main dependent variable employed in analyses that measures career success is discussed in greater detail in 4.1.3 'Dependent Variable'.

Distributions within ethnic identity categories broadly represent that of the Scottish population. At the time of the 2011 Census 92% identified as white UK, and 8% other ethnic groups (NRS, 2018a). Within this sample, 89% identified as white UK and 11% other ethnic groups. Because of a low frequencies within other ethnic groups in statistical terms, ethnicity is operationalised in analyses as a binary variable representing white UK/other. This operationalisation is employed in other studies with similar data limitations (e.g. Kramarz and Skans, 2014). Belonging to an ethnic minority group is identified within the literature as a marker of inequality in employment outcomes (e.g. Longhi and Brynin, 2017) and differential SNS use (Hargittai, 2008c).

Parental education information was collected via the survey instrument in response to occurrences of a significant influence of parental social class on social capital expenditure of young people in a career management context (e.g. Lin *et al*, 1981), and stratification of SNS use by parental education (Hargittai, 2008c). Respondents were asked about their mother and father's highest educational attainment in relation to three categories; higher education, further education, mandatory education. Respondents with one or two parents who had received a higher education are classified as having a certain level of inherited advantage, and variable operationalisation as a binary advantage/no advantage tests whether parental degree attainment plays a significant role in relevant forms of career management amongst a young sample. For older people, it has been found that constructed networks replace inherited ones (Lin *et al*, 1981), denoting important implications for the dynamics of social capital in a career management context. 54 respondents' inherited social background could not be classified using this measurement (missing data). In response, these 54 cases were imputed into the 'no advantage' category, as it was reasoned that respondents may not know the exact educational attainment of their parents, but they would be aware if they had gone on to study at university. 32% of the sample had at least one parent who had attained a higher education. Although figures exist denoting the proportion of degree-level educated adults in Scotland (26%; NRS, 2018b), the statistics do not measure adults in pairs, and are therefore difficult to compare with present measurement.

A final demographic factor measured is the language that respondents speak at home, intended to gauge level of impact of first language of career management via SNS. It is not a factor commonly identified in reviewed literature as, for example, being a barrier towards productive internet use. However language difficulties amongst immigrant populations are a mitigating factor with regards employment outcomes (Miranda and Yu, 2013; Yao and van Ours, 2015), and logically should impact ability to utilise the internet productively, on the basis of the importance of critical literacy in successful online navigation (Hargittai, 2008b), which is likely hindered by lack of language proficiency. Respondents who speak a language other than English at home total 7.2%.

To summarise the measured demographic characteristics of the sample, it cannot be considered to be generally representative of the Scottish population. This was not intended to be the case, because it is a case study of people grouped together by a specific commonality. Data is not available detailing the demographics of Scottish FE students. Chapters 7 and 8 present results from analysis of two further primary case study populations generally at more advanced stages of their working lives. Therefore Chapter 9 reflects on present results in context of a larger picture generated by the primary data.

In the Conclusions section of this Chapter (6.4), results from analysis of FE student data are reflected on taking into account implications of present sample characteristics. An oversample of rural residents perhaps offers greater opportunity to assess urbanisation as an aspect of the second-level digital divide. Findings relating to educational attainment perhaps require additional scrutiny. The younger age profile of the sample perhaps offers an opportunity to examine the role of technical competence gradations among a generally tech-savvy cohort.

6.2.2 Independent and dependent variables

The main dependent variable utilised in analyses, career positivity, is described in detail in 3.4.2.3 'Key dependent variable'. Some analyses employ different dependent variables with less frequency, that are also sometimes used as independent variables. This sub-section serves to introduce these dependent and independent variables in order to provide a brief overview of their structure for reference, and to categorise them into typologies. Typologies relate to uses of the internet, SNS use, online skill levels, and occupational success. Table 6.4 provides details of these.

Analytical theme	Variable information (Operationalisation)	Analyses used in	Frequencies and structure
Main dependent variable	Positivity regarding future career (dependent)	A1, A2, C1	0 = Not very positive **76.37%** (265) 1 = Very positive **23.63%** (82)
A: Informational SNS use	Has received information from an SNS contact regarding a job vacancy (independent and dependent)	A1, A3, B3, C2	0 = No **29.11%** (101) 1 = Yes **66.86%** (232) . = Missing **4.03%** (14)
	Has received information from an SNS contact regarding a vocational or educational course (independent and dependent)	A1, A3, B3, C2	0 = No **25.65%** (89) 1 = Yes **72.05%** (250) . = Missing **2.31%** (8)
	Has received information from a contact regarding a job, not through SNS (independent)	A2	0 = No **22.48%** (78) 1 = Yes **77.52%** (269)
	Has received information from a contact regarding a vocational or educational course, not through SNS (independent)	A2	0 = No **17.00%** (59) 1 = Yes **81.27%** (282) . = Missing **1.73%** (6)
	Skill using internet (independent and dependent)	A3, B1, B2	1 = Low **30.55%** (106) 2 = Medium **39.77%** (138) 3 = High **29.11%** (101) . = Missing **0.58%** (2)

B: Productive internet use	Has researched job vacancies online before (independent and dependent)	B2, B3	0 = No **64.84%** (225) 1 = Yes **34.29%** (119) . = Missing **0.86%** (3)
	Has researched career advice online before (independent and dependent)	B2, B3	0 = No **85.88%** (298) 1 = Yes **12.10%** (42) . = Missing **2.02%** (27)
	Has researched information regarding educational assessments online before (independent and dependent)	B2, B3	0 = No **30.26%** (105) 1 = Yes **68.59%** (238) . = Missing **1.15%** (4)
C: The strength of weak ties in career management	Selected at least one weak tie when asked to specify first three contacts that respondent would approach for career-related advice (Independent)	C1, C2	0 = No (all strong) **16.14%** (56) 1 = Yes (some weak) **82.71%** (287) . = Missing 2.63**%** (4)
	Selected at least one tie institutional staff when asked to specify first three contacts that respondent would approach for career-related advice (Independent)	C1	0 = No **49.28%** (171) 1 = Yes **49.57%** (172) . = Missing 1.15**%** (4)

Table 6.4: Details of independent and dependent variables operationalised in analyses.

Points to note regarding independent and dependent variables listed in Table 6.4 mainly relate to clarifications of how the variables are constructed, to provide additional context for related results. Of variables listed within the typology of internet uses – both productive and unproductive – some are operationalised in binary format, and others ordinal. These data were collected via a grid-style question (survey question 29) within the survey, and therefore shared a common raw format. Different coding structures are applied on a contextual basis. The context of the activity being measured was considered, as were distributions within the variable. Interactions of both considerations led to logical divergences in the coding structures. As two examples, the variable relating to reading news online is reduced to a binary format of 'does regularly/does not do regularly' firstly because news is a daily event, and respondents who stated that they read news online with less than a weekly frequency are likely using other sources primarily to read news. Secondly, relatively small frequencies occurred within the 'never', 'sometimes (1-2 times per year)' and 'semi-regularly (monthly)' categories, which reinforced the contextual choice with analytical logic. Conversely, researching financial information is unlikely to be a common daily task for most, and a more even distribution amongst original categories made an ordinal coding structure seem sensible.

When collecting data relating to SNS usage, respondents were given a definition (survey page 11) consistent with that defined within the literature review (Chapter 2), so platforms of interest such as Facebook and LinkedIn were not confused with social media, such as WhatsApp or a chat room. Consequently, indicators detailed within the 'SNS use' typology are likely more reliable in relation to the aims of this project than in, for example, Understanding Society (University of Essex, 2018a), which asks respondents if they 'belong to a social website'.

Online skill level is a self-assessment of capabilities using the internet measured through how well respondents understood terms which are related to internet use, such as 'cookies' or 'upload' (survey question 28). Five such terms were supplied, with respondents asked to rate their understanding on a 1-5 point Likert scale. Such a structure naming different terms was operationalised in Hargittai and Hinnant's (2008) study to assess internet use skill. Different terms were used presently in order to give a modern update to the measure. Respondents who self-rated as fully understanding of all supplied terms (1 on Likert scale) are classed as highly skilled. Those who on average scored between 1-2 across all scales are coded at medium skill level, and the rest low. Low is the reference category employed in analyses.

Prior to conducting analyses, all variables listed in Tables 6.3 and 6.4 were tested for collinearity. High levels would affect validity of results. Variables were first inserted into a factor analysis that identified three latent factors that variables loaded on to. These factors scored 0.53 on a Kaiser-Meyer-Olkin test, which is below the threshold for suitable inclusion of factors into models – therefore collinearity is not a concern amongst the selected variables (Crane *et al*, 1991).

6.3 Results

In Chapters 4 and 5, various employment based outcomes such as securing a position advertised online, net monthly wage and job satisfaction were operationalised as proxies of career attainment. Given the contextual conditions of this sample, such an indicator required careful consideration. Many young people studying an FE course may not have held a job related to their eventual career path. Therefore positivity for the future of respondent careers was measured via the survey instrument as a sensible compromise amongst a population that in theory, were in close proximity to their next career choice. In analyses this variable is operationalised as a binary measuring the difference between respondents who felt very positive about how their career will be going in one year's time, versus respondents who felt less positive (see 3.4.2.3 'Key dependent variable' for a fuller discussion surrounding this variable, and distribution of responses).

Before main results are presented, results from a control model constructed predicting the modal dependent variable are detailed in Table 6.5. This model predicts high levels of career positivity, functioning largely as a control model into which independent variables are inserted, providing a consistent base for these further tests.

The demographic variables normally functioning as controls also give contextual detail regarding factors that predict high levels of positivity through operationalisation as independent variables.

DV = Very positive about career in one year's time	Control model
Age	.01
High education	-.80*
Medium education	-.54ᶧ
Female	-.22
BME	.47
Rural	-.16
Non-English first language	-.51
Advantaged social background	.09
BIC =	399
R2 =	.02
Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001	

Table 6.5: Control model predicting very high levels of career positivity. N = 323.

Results suggest that education is the only factor having a significant impact in predicting high levels of career positivity. In analyses replicating the control model where the dependent variable has been structured differently – for example an ordinal logistic regression predicting the career positivity variable in 5-point Likert scale format – results are not significantly different. The coefficient estimates for highest educational attainment suggests a negative effect that an average rises with higher qualification levels (through a significant coefficient for a high level of education, and the coefficient for a medium level approaching significance). This education effect connotes either one of two things. That respondent career positivity is a quirk of this particular career-stage context, or that it is not a clear-cut proxy of career success, given education is the best (positive) predictor of UK wage levels (Hayward *et al*, 2014; Naylor *et al*, 2015).

6.3.1 Analytical Theme A: Informational SNS use

Following identification of a bonus of SNS use on career outcomes in Chapter 4, which supported Rainie and Wellman's (2012) identification of such platforms as supportive to career attainment through generation and management of social capital, results are presented within this section that test for such trends amongst the present sample of young students. Bespoke data collection enables inclusion of additional detail in these tests identifying specific types of information received from contacts via SNS. This section then, focuses on potential informational bonuses gained through SNS use, adding detail to related trends identified in previous Chapters.

To test the efficacy of SNS use to gain information beneficial to career management, three models were constructed predicting career positivity as a proxy outcome for successful career management (Analysis A1). Independent variables employed are; receipt of information from a contact via SNS regarding a job vacancy (Model 1), receipt of the same information through another channel (model 2), and both independent variables net of each other (model 3). Receipt of information through both channels are modelled net of one another in model 3 to test SNS efficacy within use of social capital. Control model results predicting a high level of positivity are included for comparison.

DV = Very positive about career in one year's time	**Control model**	**A1 (model 1)**	**A1 (model 2)**	**A1 (model 3)**
SNS job vacancy info		.51ᵻ		.11
Other mode job vacancy info			.89*	.81ᵻ
R2 =	.02	.03	.04	.04
BIC =	408	415	412	418
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 6.6: Analysis A1. Logistic regressions predicting impact of gaining information regarding a job vacancy from an SNS contact (model 1) and receiving information from a contact via a different mode regarding a job vacancy (model 2) on very high levels of career positivity, and both information receipt modes modelled together (model 3). N = 339, all net of controls listed in Table 6.5.

Model 1 does not find receipt of job vacancy information from an SNS contact to significantly predict very high levels of career positivity. The coefficient estimate of a positive effect is approaching significance. Model 2 finds receipt of such information via another mode to have a significant and positive effect on likelihood of very high levels of career positivity. When both independent variables are tested net of each other, no significant effects are found – although receipt of job vacancy information via a mode other than SNS is estimated as a positive effect approaching significance.

Although r2 values increase sequentially through the models, the BIC figures do also, denoting a lack of utility of the models generally in predicting levels of career positivity. Results suggest that SNS use for gaining information about job vacancies does not grant a bonus to career management. However there is limited evidence suggesting that social capital use when enquiring about job vacancies does help, through association with respondents who feel very positive about their future careers.

Additional tests (Analysis A2) were carried out comparing the dichotomies (SNS/offline) of information channel, due to the context of the sample. Logically, it is likely that many such job vacancies that respondents received information from contacts regarding were casual jobs unrelated to career paths. Models 1, 2 and 3 (Table 6.7) repeat the structure of analyses detailed in Table 6.6 (Analysis A1) in context of information received from contacts regarding educational or vocational courses, which are arguably more important in career management for younger people.

DV = Very positive about career in one year's time	Control model	A2 (model 1)	A2 (model 2)	A2 (model 3)
SNS education + training info		.68*		.77*
Offline education + training info			.16	-.22
R2 =	.02	.03	.02	.03
BIC =	402	404	408	409
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 6.7: Analysis A2. Logistic regressions predicting impact of gaining information regarding an educational or vocational training course from; an SNS contact (model 1), a contact through another mode (model 2) on very high levels of career positivity, and both information receipt modes modelled together (model 3). N = 328, all net of controls listed in Table 6.5.

Model 1 finds that educational or vocational information received from a contact via SNS has a positive and significant effect on a high level of career positivity, although the BIC value increases from the precursor model (control model). Receipt of such information via another mode is not found to significantly effect career positivity. In model 3 this coefficient estimation for SNS information stays relatively consistent with the addition of information received offline. Receipt through another mode information is also not significant. These results provide support for hypothesised boosts to career management through use of SNS to gain valuable and original information from contacts. They also suggest that when social capital is used, SNS are a particularly useful channel to get the information through.

Given identification of possible boosts to the career success proxy through informational SNS use, and more clear-cut findings of this nature in Chapter 4, tests exploring the nature of the second-level digital divide in this context are pertinent. Analyses presented in Chapter 4 also found a significant and positive impact of skill levels in predicting attainment of more prestigious online-advertised jobs. In that data, skill was measured via self-assessments of respondent abilities in two areas – confidence in using technology and ability to determine reliability of online source material (critical skill). The trends found in Chapter 4 affirmed findings within wider research literature, which identify user skill as an attribute that mediates between productive internet use and structural inequality (e.g. Hargittai and Hinnant, 2008). For example people with lower levels of education also have lower levels of skill in which to utilise productive functions of the internet.

One indicator measures users' skill in using the internet presently. This indicator - a 3-category ordinal variable depicting high, medium and low self-rated skill - is employed to predict receipt of information through SNS (Analysis A3). Model 1 focuses on information regarding a job vacancy, and model 2 information regarding an educational or vocational course. Control models predicting receipt of the respective forms of information minus inclusion of the skill indicator are included in Table 6.8 for reference.

Table 6.8:

Dependent variables = information received through SNS contact		Control model (information = job vacancy)	A3 (model 1)	Control model (information = educational or vocational training course)	A3 (model 2)
Online skill	High		-.25		.39
	Medium		-.27		-.12
R2 =		.04	.04	.03	.03
BIC =		462	472	417	427
N =		335	335	327	327
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001					

Analysis A3. Logistic regressions predicting impact of online skill on receipt of information from an SNS contact regarding; a job vacancy (model 1), an educational or vocational training course (model 2). All net of controls listed in Table 6.5.

Results of Analysis A3 suggest that the null hypothesis cannot be rejected. Skill level is not found to have a significant impact upon receipt of either form of information through SNS. Model fit statistics do not improve when the skill indicator is added to both control models.

Results pertaining to Analytical Theme A are not clear cut. Informational use of SNS is tested both in relation to career management, via the career positivity outcome, and the second-level digital divide via self-rated internet skill levels. In relation to career management, SNS are not found to be a useful tool within social capital management for receiving information related to job vacancies. They are however found to provide a boost to career positivity in context of receiving information regarding human capital development (educational or vocational training course). When considering the sampling context, it is perhaps information regarding courses which is most likely to be relevant to career management for respondents, given many are young who may have only worked in casual ‘student jobs’.

Skill level is not found to be a factor that influences likelihood of receiving either type of information. It could perhaps be the case that differentiation in skill levels is less marked than within the general population. The theory of digital natives (Prensky, 2001) implies that young people are generally competent internet users when compared to older generations. The role of skill level within productive internet use is explored further in the next section.

6.3.2 Analytical Theme B: Productive internet use

The present section presents and discusses results from tests within Analytical Theme B (see Table 6.2). Expanding the investigation of the role of the second-level digital divide within career management, it builds upon analyses documented in the previous section. Results presented within the previous section suggest that SNS are perhaps a useful tool for gaining information from social contacts, but this is not clear. They also suggest that that online skill levels play a role in this process. The next tests assess what the research literature hypothesises plays a part in the wider question of how beneficial SNS are to career management.

First (in Analysis B1), determinants of a high level of internet skill are explored. Factors such as education level (e.g. Hargittai and Hinnant, 2008), and age (Prensky, 2001) are found to impact skill levels – greater education level positively, and higher age negatively. In Analysis B2, internet skill is then operationalised to test whether skill levels impact productive uses of the internet in a career management context (e.g. van Duersen and van Dijk, 2014), as a rebuttal to Rainie and Wellman’s (2012) conceptualisation of social networking sites as egalitarian forces in career attainment. A third set of analyses test whether these productive internet uses affect career outcomes, as logic would dictate. Finally, productive internet uses are operationalised to predict receipt of beneficial information from an SNS contact, in an expanded investigation of the role of the second-level digital divide. A similar analytical path is followed using Oxford Internet Surveys data (Chapter 4), which identified a skilled online population who utilised the internet productively and also appeared to gain hypothesised benefits of SNS use.

In analysis B1, a dummy variable operationalising respondents who self-rated as having a high level of internet skill (‘1’) as opposed to other self-ratings (‘0’) is operationalised as the dependent variable. Controls consistent with those applied throughout this chapter are employed as independent variables. Results are listed in Table 6.9.

DV = High level of online skill	B1 (control model)
Age	.02
High educational attainment	.38
Medium educational attainment	.08
Ethnic minority	-.74
Female	-.96***
Urban	-.10
Advantaged inherited background	.05
Non-english first language	.14
N =	335
Psuedo R2 =	.05
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001	

Table 6.9: Analysis B1. Logistic regression operationalising control variables to predict a high level of online skill amongst respondents.

Results largely differ from those within second-level digital divide literature. Factors such as age and education which are specifically identified as proxies of differential skill levels are not found to have a significant impact. Women are found to be significantly less likely to self-rate as having a lower level of internet skill, however. Although one study reviewed finds gender (male) to be a significant predictor of ‘advanced interaction with the internet’ (Helsper and Enyon, 2010) – which theoretically is enabled by higher skill levels (van Deursen and van Dijk, 2014) – it is not widely identified within second-level digital divide literature. As suggested earlier, differential findings presently could represent a cohort effect with reference to the theory of digital natives (Prensky, 2001). Alternatively, lack of harmony with research literature could hint at a measurement issue.

Although online skill has not been found to effect career management processes presently, it is still worthwhile to explore its role further. Analysis B2 employs the high online skill indicator as an independent variable within a set of regression models, predicting three productive uses of the internet separately. These uses are career-related and indicate whether respondents have used the internet in these ways before, compared to not having done so; to look for job vacancies, to look up career advice, and to research information pertaining to assessments. Studies focusing on the second-level digital divide find vocational, or productive uses of the internet are predicted positively by skill level (e.g. van Duersen and van Dijk, 2014). Table 6.10 displays Analysis B2 results.

		B2 (model 1, DV = Look online for jobs)	B2 (model 2, DV = Research educational or vocational course online)	B2 (model 3, DV = Research assessment information)
Online skill level:	High	.45	.51	.08
	Medium	.43	-.19	-.22
N =		334	331	333
Psuedo R2 =		.02	.05	.06
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 6.10: Analysis B2. Logistic regression models employing high level of online skill as independent variable, predicting use of the internet to; look online for jobs (model 1), research educational or vocational course information online (model 2), and research assessment information (model 3), all net of controls listed in Table 6.5.

Online skill level is not found to impact upon operationalised productive internet uses in Analysis B2. Therefore, in common with other results presented so far, no identification of second-level digital divide processes has been found within a career management context.

One caveat to consider regarding the independent variables in Analysis B2 of is in meaning attached by respondents. The phrase 'researching financial information' was presented as such in the survey to represent research regarding original financial information that indirectly helps with career management, such as information on benefits, or average salaries in an industry. Despite the careful wording, there is possibility that it could be taken to include checking bank balances online. If this were the case, it may follow logically that FE students with jobs were more likely to check bank balances, which would in turn particularly influence model results.

The final set of analyses carried tests links between productive internet use and receipt of potentially beneficial information from an SNS contact. This link was suggested by results from analysis of Oxford Internet Surveys data, and is also implied through the notion of a second-level digital divide – that potential benefits of career management online are reaped by those with a requisite skill level. Results from models 1-3 (Analysis B3) predicting receipt of information from an SNS contact regarding a job vacancy, net of controls.

DV = Received information from SNS contact regarding job vacancy	B3 (Model 1. IV = Look online for jobs)	B3 (model 2. IV = Look up career advice)	B3 (model 3. IV = Research assessment information)
Independent variable	.63*	1.38**	.70**
Pseudo R2 =	.05	.06	.05
N =	334	331	333
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 6.11: Analysis B3, models 1-3. Logistic regression models predicting respondents who had previously received information from an SNS contact regarding a job vacancy. Independent variables; has looked online for jobs before (model 1), has researched information regarding an educational or vocational course online before (model 2), and has researched career advice online before (model 3). Net of control variables listed in Table 6.5.

A link between all three productive internet uses and receipt of potentially beneficial information from an SNS contacts regarding a job vacancy is found. These have a positive relationship with receipt of information from an SNS contact. This implies a link between different productive online behaviours, although this is the first set of analyses to do so. Further models (4-6) repeat models 1-3, operationalising receipt of information regarding training courses as dependent variable. These results are detailed in Table 6.12.

DV = Received information from SNS contact regarding ed/voc course	B3 (Model 4. IV = Look online for jobs)	B3 (model 5. IV = Look up career advice)	B3 (model 6. IV = Research assessment information)
Independent variable	.65*	.84ᵻ	.73*
Pseudo R2 =	.05	.04	.05
N =	326	325	327
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 6.12: Analysis B3, models 4-6. Logistic regression models predicting respondents who had previously received information from an SNS contact regarding an educational or vocational course. Independent variables; has looked online for jobs before (model 4), has researched information regarding an educational or vocational course online before (model 5), and has researched career advice online before (model 6). Net of control variables listed in Table 6.5.

Similar results are generated to models 1-3 in models 4-6 within Analysis B3. Previous use of the internet to look online for jobs and to research assessment information is found to have a significant and positive predictive relationship with receipt of the second form of potentially valuable information via an SNS contact. Looking up career advice online previously however is not found to impact the outcome at a significant level.

Results from Analysis B3 present a compelling link between productive SNS use, and productive use of the internet more generally. Although little evidence has been found thus far relating to second-level digital divide factors playing a mitigating role within SNS use in relation career management, results from the present set of analyses do suggest the existence of a population who use both SNS and the internet more generally in a productive fashion.

This productivity however, is not found to be predicted by online skill levels. Moreover, skill level is not found to be reflective of factors discovered within the research literature, such as education (Hargittai and Hinnant, 2008). In attempting to understand patterns within this data, the inference that a cohort effect, where less variation exists amongst skill levels as a result of technological ubiquity in the formative years of younger people (Prensky, 2001), seems fairly plausible.

6.3.3 Analytical Theme C: The strength of weak ties in career management

A benefit of collecting primary data was the ability to design questions via the survey instrument that allowed for the possibility of generating analyses that assessed contact influence on career management by tie type. Secondary social survey data suitable for use in this project did not enable such gradations. These tests are designed to explore an intersection within the research literature. Following the work of key social capital researchers such as Mark Granovetter (1973) and Nan Lin (1999), Rainie and Wellman (2012) envisaged the real potential of SNS lay in the way that users could develop and maintain support networks of weak ties. Relationships characterised by lightweight contact that did not incur traditional networking costs of formation and maintenance.

Variables under the typology of 'informational ties' required conceptual input in construction regarding classifications of ties. Respondents were given a list of 11 relationship descriptions with which to classify the first three people they could approach for career-related advice, including an 'other' option (Appendix 1c; question 25). Online or offline contact was not specified. Most relationship types fell neatly into weak-or-strong tie categories on the basis of literature precedent (e.g. Granovetter, 1973; Lin, 1999). 'Other family member', as opposed to 'close family member', is more difficult to classify. Studies do operationalise non-immediate family members as close ties (e.g. Kramarz and Skans, 2014), although distant relatives where relationships are characterised by very infrequent contact are a distinctly different type of contact to a sibling that one shared a home with in their formative years. Therefore, other family members are operationalised as 'other family members' in this research. In addition, a derived variable was constructed denoting a tie choice of 'tutor/member of staff at college', in order to test for any additional effect that access to institutional weak ties has in career management for FE students. Table 6.13 provides full detail of the tie coding process.

Strong ties	**Weak ties**	**Institutional ties**
Partner	Other family member	Tutor/member of staff at college
Close family member	Someone from course	
Close friend	Work colleague	
	Distant friend/acquaintance	
	Friend of a friend	
	Tutor/member of staff at college	
	Friend of a family member	
	Other	

Table 6.13: Classification of relationships yielding career advice by tie type. 'Tutor/member of staff at college' classified as institutional tie in additional derived variable (see Table 3).

Two indicators are derived for inclusion in Analysis C1. The first does not account for institutional ties, instead coding such contacts as weak ties. It measures selection of at least one weak tie in the career-information networks of three contacts, as opposed to selection of all strong ties. This is used to predict a very high level of career positivity amongst respondents (model 1), in order to explore weak tie utility in career management. Only a relatively small sample proportion (16%) said that they would request career-related advice from strong ties in the first three instances. The second indicator measures selection of any institutional ties versus others to predict very high levels of career positivity (model 2). Selection of institutional ties within career-related information networks was common – 50% of respondents selected at least one. Model 2 is a test that gauges the importance of this particular form of weak tie within career management.

DV = Very positive about career in one year's time	Control model	C1 (model 1 – at least one weak tie)	C1 (model 2 – at least one institutional tie)
Tie selection		-.37	.43
BIC =	406	411	409
R2 =	.02	.02	.02
Key: ˈ **p<0.1 * p<0.05 ** p<0.01 *** p<0.001**			

Table 6.14: Analysis C1. Logistic regression predicting respondents being very positive about their career in one year's time with selection of at least one weak tie in career information networks (model 1) and selection of at least one institutional tie (model 2) as independent variables. Net of controls listed in Table 6.5. N = 333.

Results of Analysis C1 suggest tie type does not influence the career success proxy. Moreover, inclusion of selection of weak ties and selection of institutional ties within career information networks worsens control model fit statistics, suggesting that tie choice does not help explain career positivity.

Analysis C2 tests the relationship between valued weak ties and receipt of potentially beneficial information via an SNS contact is tested for. The indicator denoting selection of at least one weak tie within career information networks is again operationalised as the independent variable. Receipt of potentially beneficial information via SNS regarding a job vacancy (model 1) and an educational or vocational course (model 2) are employed as dependent variables. A significant and positive relationship would suggest that SNS may play a role in the cultivation of this valuable weak-tie social capital. If results suggested this was the case, career positivity as a proxy of career success would appear flawed, due to contradictions in results. If results supported the null hypothesis, the conclusion of these tests would be that tie choice does not make a difference in career management amongst this sample. Table 6.15 documents the results of interest from Analysis C2. Control model statistics predicting respective forms of information received are displayed for reference.

DV = Information received via SNS	Control model (job vacancy information)	C2 (model 1)	Control model (educational or vocational training course information)	C2 (model 2)
Valued weak ties		-.42		-.89*
BIC =	459	463	416	416
R2 =	.04	.04	.03	.05
N =	333	333	325	325
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 6.15: Analysis C2. Logistic regressions predicting receipt of information from an SNS contact; relating to a job vacancy (Model 1), and to an educational or vocational training course (model 2). Independent variable = selection of at least one weak tie within career information networks. Net of controls list in Table 6.5.

Career information networks containing weak ties within the top three contacts are found to negatively predict likelihood of receiving advice about courses amongst FE students in model 2. However, model 1 results find no significant impact of valued weak tie access on receipt of job vacancy information via SNS. Therefore analysis suggests that SNS use to manage weak tie relationships does not lead to greater likelihood of receiving potentially valuable information. On the contrary, model 2 results suggest that access to valued weak ties for career-related advice reduces likelihood of respondents receiving potentially valuable information through SNS.

Because tie selection is not suggested to positively influence career management through present results (Analysis C1), additional analysis addressing Research Question B3 are not performed. Such analyses would explore stratification of effects of access to valued weak tie social capital, in response to findings within the research literature which suggest weak tie access, and returns from use are unevenly distributed (Ericksen and Yansey, 1980; Kramarz and Skans, 2014).

Although findings relating to this section must be caveated with the recognition that 3 tie choices to approach for career advice do not constitute a whole network, and therefore the informational ties indicator employed throughout analyses in this sub-section is imperfect. Informational tie choice was not shown to impact levels of positivity regarding future careers however, and additionally choice of weak ties was found to reduce likelihood of receipt of potentially valuable information via SNS. Receipt of this particular form of information in question – regarding educational or vocational training – was found to have a positive effect on positivity in results from Analysis A2. Therefore evidence tentatively suggests that strong ties, as opposed to weak, are perhaps more closely associated with successful career management within this sample. Taking into account the age profile of the sample, these results could be reflective of FE student reliance on ascribed strong tie networks, which in the literature significantly influence career outcomes (e.g. Moerbeek *et al*, 1995) before constructed networks begin to have greater influence with advancing age (Lin *et al*, 1981).

6.4 Conclusion

Prior to synthesis of findings in relation to research questions and wider literature, limitations must be considered as context. First, the sole outcome representing the result of successful career management – career positivity – may not be considered the most robust indicator possible. It is perhaps why certain tests did not produce hypothesised results. Contextually however, this perhaps serves to highlight the difficulty in attempting to assess career trajectories of respondents of such a young aggregate age. Another measurement issue potentially arose when attempting to gauge respondent internet skill levels. The skill level indicator did not perform as expected in any tests that it was included in, despite results involving other key theoretical planks of the utility of SNS within career management suggesting that a linking factor within internet and SNS use did exist. For example, productive internet use was found to significantly predict likelihood of receiving potentially valuable information from SNS contacts regarding human capital development (courses). Courses in turn were found to significantly predict high levels of positivity regarding the future careers of respondents, suggesting the existence of a relatively productive set of SNS and internet users who experienced career management benefits.

The sample is also not representative of the wider population. This however is an intended consequence of the research design, and findings are considered in context of general population representativeness in Chapter 9. Nonetheless, biases were found within the sample that suggest it is likely not representative of the Scottish further education student population, such as an oversampling of rural residents.

6.4.1 Research Question A: Does SNS use benefit career management?

Findings tentatively support the notion of SNS utility in career management when sample context is considered. Absence of indicators representing some key theoretical planks behind the notion producing results consistent with a review a relevant literature means conclusions are not straightforward.

Receipt of information considered potentially valuable to career management was operationalised to represent hypothesised benefits of social capital management via SNS (Rainie and Wellman, 2012). Information about jobs when coming from an SNS contact was not found to have any utility, although information from the same channel regarding a course was linked to successful career management. It is quite possible that this is because for young people yet to embark in earnest on their careers, jobs represent a means to fund living costs, rather than a career management consideration. Wider productive use of the internet was also found to be linked to productive SNS use, in the form of receiving information regarding courses.

Utility of weak ties within career management (Granovetter, 1973) was not replicated in findings. Respondents who placed value in weak ties (as well as institutional ties – for example course tutors), were not found to be more likely to experience preferential career management outcomes. Tentative evidence was found of the inverse – that those with access to valued weak ties are less likely to reap the hypothesised benefits of SNS use.

6.4.2 Research Question B: Who embraces the potential effects of SNS use?

The key mediating factor between experience of inequality on-and-offline within the research literature is consistently identified as skill level (Hargittai, 2008a; Hargittai and Hinnant, 2008; van Deursen and van Dijk, 2014). Skill level was not found to be a significant factor in predicting productive SNS use or more general productive internet use, nor was it found to mediate in relationships with successful career management outcomes.

Some findings hinted at the existence of the second-level digital divide operating within the themes of analysis though. In particular consistent evidence linking productive SNS use with productive use of the internet more generally serves as compelling evidence of a stratification of users. It seems likely in this context that the measurement of skill level operationalised failed to identify this population, despite it being constructed according to literature precedent (Hargittai and Hinnant, 2008). A lack of clear identification of second-level digital divide factors is perhaps a result of the younger age profile of the sample, who theoretically should be relatively savvy internet users (Prensky, 2001), and therefore perhaps a relative lack of variation in skill level prevented the reproduction of conventional findings.

Stratification of effects relating to weak tie use within career management (e.g. Moerbeek *et* al, 1995) was not tested due to no identified effects of weak tie use generally.

Chapter 7 – Mothers of young children

7.1 Introduction

Chapter 7 presents and discusses results from analyses of primary data collected from the second of three sample case studies. Parents of young children were identified as a compelling site for analysis because the added complexity that raising children – particularly of a young age – can bring to the management of a career. The birth of a child brings maternity leave, either statutory or extended, and beyond that careers usually have to be managed with reflection on childcare considerations (Hakim, 2004). Whereas Chapter 6 is situated in context of further education students generally at the start of their career journey, Chapter 7 respondents are generally further on in their careers, although not close to retirement.

Originally the case study was not intended as gender-specific. Parents of any gender were invited to take part, but few male respondents took part (5%). Since it is expected that gender is an important factor in career management issues for parents of young children, but the male subsample would lack statistical power, male responses are omitted from analysis. Further details relating to data collection are found in *3.4.3*.

7.1.1 Literature overview

Social capital is identified as a form of capital in its own right, which interacts with other forms, such as cultural capital (Bourdieu, 1986). It is instrumental in career management as an unlocking mechanism that can lead to information critical to gaining new positions (Granovetter, 1974; Lin, 1999), greater compensation in roles (Burt, 2004), and decreased likelihood of early exit from employment (Bonoli and Turtschi, 2015). SNS are viewed by some influential commentators as modern enablers of equality of opportunity, through the reduction of costs traditionally inhibitive to the development and maintenance of a diverse network of loosely-knit ties (Rainie and Wellman, 2012).

Previous research finds a relationship between the closeness of relationships and the utility of information received, in context of career management. Weaker ties, such as acquaintances, provide more useful information than closer relations (Lin and Dumin, 1986). Further, informational benefits associated with weaker ties are not uniform across the population. Characteristics such as ethnicity (Green *et al*, 1995) and educational attainment (Ericksen and Yansey, 1980) have been identified as markers of differential levels of social capital, and effects of instrumental use.

In opposition to Rainie and Wellman, other scholars believe the opportunity-equalising benefits of SNS and wider internet space are over-hyped. As in the physical world, structural circumstances inhibit the ability of internet users to unlock potential benefits. As such, the ‘second-level digital divide’ (Hargittai, 2008a) considers a spectrum of differentiated usages and outcomes associated with the proportion of the population that has access to the internet.

Research relating to utility of SNS in career management for mothers was not found through the literature review. Some studies however test key theoretical planks of the hypothesis though. SNS have been found to be an important source of social support for mothers (Nolan *et al*, 2015), although this study is not conducted within the context of career management. Other research is consistent with research which identifies experience of inequality for women in relation to social capital (e.g. McPherson and Smith-Lovin, 1982). Farrie and Press (2005) found that mothers who named other women as contacts with whom they discussed important matters were more likely to be in low-paid service work. Another study found that women with greater access to weak ties are more likely to be in paid employment, and that disadvantaged mothers were more likely to require assistance from social networks to enter the labour market (Stoloff *et al*, 1999).

7.1.2 Research questions addressed

A description of analytical themes and the research questions that each addresses are provided in this sub-section for reference. Table 7.1 restates Thesis research questions outlined in *2.8.2*.

Research Question A: **Does SNS use benefit career management?**	**Research Question B:** **Who embraces the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	**B1)** Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	**B2)** Who uses the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	**B3)** Is there an uneven distribution of positive, career-outcome effects from weak tie social capital use?

Table 7.1: Thesis research questions.

Table 7.2 describes how three analytical themes in context of career management are assessed in this chapter: SNS use and social capital; an exploration of the second-level digital divide; and the closeness of ties. Grouped into these themes, topics of individual analyses are detailed in relation to the research question that they address. A summary of the way indicators of these questions are operationalised in the analytical models is also included.

Analytical theme	Analysis question	Modelling strategy	Research question(s) addressed
A: Social capital and SNS in career management	**(A1)** Does SNS use provide a career management boost?	2 models: Receipt of information from an SNS contact predicting career optimism	Research Question A1-3
	(A2) Does social capital use help career management?	2 models: Receipt of information from a contact (not via SNS) predicting career optimism	Research Questions A1, A3
	(A3) Does online skill level effect receipt of information through SNS?	2 models: Self-rated online skill level predicting receipt of two forms of information through SNS	Research Question B1
B: Online skill and the second-level digital divide	**(B1)** What personal characteristics effect online skill?	1 model: High level of online skill predicted by personal characteristics (control variables)	Research Question B2
	(B2) Does a high level of online skill predict other productive uses of the internet?	3 models: High level of online skill predicting 3 proxies of productive internet use	Research Question B2
	(B3) Are productive internet uses predictive of positive career outcomes?	3 models: 3 proxies of productive internet use predicting career optimism	Research Question A3
	(B4) Are productive internet uses predictive of receipt of career-related SNS information?	6 models: 3 proxies of productive internet use predicting receipt of 2 forms of career-related information via SNS	Research Questions A1, A3
	(C1) Are weak tie career information resources associated with better employment outcomes?	1 model: Naming of 1 weak tie or more within top 3 career information contacts predicting career optimism	Research Question A2 (in conjunction with analysis C2)

C: Weak ties and career management	**(C2)** Are respondents with more valuable weak tie resources more likely to receive career-related information via SNS?	2 models: Naming of 1 weak tie or more within top 3 career information contacts predicting receipt of 2 forms of career information via SNS	Research Question A2 (following from Analysis C1)
	(C3) Are the effects of weak tie social capital unevenly distributed?	3 models: C1 repeated three times, each model featuring an additional interaction between selection of weak ties in top 3 career information contacts and degree attainment, high inherited social status, male CAMSIS scores respectively	Research Question B3

Table 7.2: Analytical structure details and research questions addressed.

Further discussion of analyses takes place in respective results sections. Collectively analyses address all project research questions.

7.2 Sample characteristics

The sample is composed of 152 mothers who, at the time of data collection, had at least one child of primary school age (generally 5-12 in Scotland; European Commission, 2018). The child age parameters are set firstly to capture responses from mothers with children who do not require care all day (as they are in school). Therefore the likelihood that respondents will have engaged with career management strategy relatively recently is increased. Some do however have additional younger children. It was deemed too restrictive to screen such mothers out of the survey. Secondly, the upper child age limit is applied to offset concern over problems of recall surrounding survey questions about when a respondent's children were younger. Respondents were recruited mainly via social media adverts posted by family or parenting charities. Therefore respondents are assumed to have some level of involvement or interest in the work of charities approached. This work is varied and targets a range of people, but is linked by a focus on children and families. Further details of respondent recruitment are found in section 3.4.3. Table 7.3 provides details of sample characteristics that develop the context that the analyses are situated within.

Characteristic	Categories	% of sample (freq.)	% of valid sample (if some data missing)
UK region	Scotland	92.76% (141)	
	Northern Ireland	1.32% (2)	
	East of England	2.63% (4)	
	London	0.66% (1)	
	South East England	1.97% (3)	
	South West England	0.66% (1)	
Tenancy type	Own outright	6.58% (10)	
	Own with mortgage	56.58% (86)	
	Private rent	15.13% (23)	
	Social housing	21.05% (32)	
	Other	0.66% (1)	
Number of children	1	17.11% (26)	17.45%
	2	55.26% (84)	56.38%
	3	16.45% (25)	16.78%
	4+	9.21% (14)	9.40%
	Missing data	1.97% (3)	
Lives with a partner	Yes	78.95% (120)	
	No	21.05% (32)	

Table 7.3: Sample information. N = 152.

Responses from residents in Scotland (93%) were targeted during survey dissemination. The proliferative nature of social media however, exposed the survey to non-Scottish residents and responses from people who live in other parts of the UK were not excluded (7%). The modal categories for tenancy type are owning a property with a mortgage (57%), and for number of children, two (55%). Almost 80% of mothers live with a partner. Sample tenancy arrangements are broadly consistent with the population, although a little above average for owner occupation (sample = 63%, Scotland = 58%; Scottish Government, 2017). Representativeness of the wider Scottish population is better assessed also taking into account other sample characteristics. Table 7.4 details further characteristics which are operationalised in analyses as control variables.

Variable description (coding detail if different in analyses)	Category	% of sample (freq.)	% of valid sample (if some data missing)
Highest educational attainment (dummy binary variable indicating degree or higher attainment in analyses)	Degree or higher	65.79% (100)	66.23%
	Post-secondary	22.37% (34)	22.52%
	Compulsory secondary	11.18% (17)	11.26%
	Missing data	0.66% (1)	
Ethnicity (binary 0 'White UK', 1 'Other' in analyses)	White UK	84.87% (129)	87.16%
	White other	10.53% (16)	10.81%
	Asian	0.66% (1)	0.68%
	Mixed race	1.32% (2)	1.35%
	Missing data	2.63% (4)	
Parent with a degree: Inherited social advantage	Yes	38.82% (59)	
	No	61.18% (93)	
Urban density	Urban	52.63% (80)	53.33%
	Rural	46.05% (70)	46.67%
	Missing data	1.32% (2)	
Age: Mean = 38.49| Std. Dev. = 5.85 | Range = 26-53 | Skewness = .10 Missing = 1.97% (3)			

Table 7.4: Sample characteristics operationalised as control variables in analyses. N = 152.

Two factors in Table 7.4 suggest an over-representation of respondents from relative social advantage. First, 66% of respondents have a degree-level education (or higher), which is much higher than that of the Scottish population recorded in the 2011 Census (26%, see National Records of Scotland, 2016). Even accounting for the growing number of people undergoing a higher education in the UK after post-1992 structural reform (Tomlinson, 2008; ONS 2016), who have attended university since 2011, the sample over-represents well-educated people. Second, the sample unintentionally excludes older members of the working population and retired people through child age boundaries. Older people are more likely own their home via mortgage or outright in the UK (House of Commons Library, 2017). Although it is debateable whether home ownership is a good proxy of social advantage, it is generally seen as the most desirable mode of tenancy in the UK (NatCen, 2017). Therefore the high rate of home ownership and degree-level educational attainment amongst a young sample suggests relative advantage of the sample at the aggregate level.

Educational attainment is operationalised as an important control primarily due to its predictive relationship with differential uses of the internet and associated outcomes (e.g. Wei and Hindman, 2011). This operationalisation is carried out in a binary format, depicting degree-level or above attainment versus lower educational attainment. This decision is made due to a lack of cases within the mandatory secondary education category. Age is also viewed as an important factor within the second-level digital divide through the theory of ‘digital natives’ (Prensky, 2001).

Like educational attainment, ethnicity is reduced down to a binary variable (white British/rest) due to low case numbers in other categories. Black and minority ethnic cases are particularly low (2%), which under-represents these groups in Scotland, but not by much. Black and minority ethnic groups (non-white) made up 4% of the Scottish population in 2011 (National Records of Scotland, 2018a). This variable is of interest primarily because of social capital deficits, and return deficits from instrumental use within career management (e.g. Verhaeghe *et al*, 2013). This operationalisation is employed in other studies with similar data limitations (e.g. Kramarz and Skans, 2014).

Parental education information was obtained via the same mechanism as with further education students (Chapter 6), to gain a measure of inherited social privilege for respondents. Respondents with at least one parent who attained a degree-level education or higher are coded separately to those without a parent who gained a degree. Respondents classed as inheriting a level of social privilege (39%) are outnumbered by those who have not (61%). Representativeness is difficult to ascertain, as only statistics denoting degree-level attainment for individuals are publicly available. 26% of adults in Scotland have attained a degree (National Records of Scotland, 2018b). 7 missing data cases within this variable are imputed to the category indicating no parental degree attainment, as it is assumed respondents would know if their parents studied at university. This data was collected as previous research shows that young adults gain a boost to employment outcomes through parental/familial social capital (e.g. Lin *et al*, 1981).

Finally urban density is employed as a control variable because of slower broadband speeds in rural areas (Ofcom, 2018b), that could inhibit autonomy of internet use. Autonomy of use has been identified as a predictor of productive internet activity (Hargittai and Hinnant, 2008). Urban residents are slightly more prevalent within the valid sample (53%). The rural figure (47%) oversamples rural residents. Official figures show that around 17% of the Scottish population lives within rural areas (Scottish Government, 2018). A similar level of over-sampling is found in further education student data collected using the same measurements. Therefore it appears very likely a result of measurement issues, rather than a random chance over-sampling.

7.2.1 Independent and dependent indicators

In common with chapter 6, a measure of how optimistic respondents feel about their career at the present times (for FE students, in one year's time) is employed as the main dependent variable within the analytical framework. This was deemed the most appropriate measure of successful career outcomes amongst a population who are probably less likely to be in work, and more likely to be in a more casual employment arrangements than the general population, due to the conflict between caring for a young child and career management (Hosking and Western, 2008). This conflict, it was reasoned, affects the validity of more conventionally used employment outcomes such as wage levels (e.g. Ericksen and Yansey, 1980), or occupational status (Lin *et al*, 1981). This main dependent variable is also discussed in 3.4.3.4, and its distribution is provided in Table 7.5. Table 7.5 also details all other independent and dependent variables operationalised in analyses reported within this chapter. These are arranged according to their modal analytical theme, outlined in Table 7.2.

Analytical theme	**Variable information (Operationalisation)**	**Analyses used in**	**Frequencies and structure**
Main dependent variable	Career optimism (dependent)	A1, A2, B3, C1, C3	0 = Not optimistic **59.21%** (90) 1 = Optimistic **39.47%** (60) . = Missing **1.32%** (2)
A: Social capital and SNS in career management	Has received information from an SNS contact regarding a job vacancy (independent and dependent)	A1, A3, B4, C2	0 = No **57.89%** (88) 1 = Yes **42.11%** (64)
	Has received information from an SNS contact regarding a vocational or educational course (independent and dependent)	A1, A3, B4, C2	0 = No **49.34%** (75) 1 = Yes **50.66%** (77)
	Has received information from a contact regarding a job, not through SNS (independent)	A2	0 = No **49.34%** (75) 1 = Yes **50.66%** (77)
	Has received information from a contact regarding a vocational or educational course, not through SNS (independent)	A2	0 = No **31,58%** (48) 1 = Yes **68.42%** (104)
	High level of online skill: Self-rated (independent and dependent)	A3, B1, B2	0 = No **73.03%** (111) 1 = Yes **25.00%** (38)

			. = Missing **1.97%** (3)
B: Online skill and the second-level digital divide	Has researched job vacancies online before (independent and dependent)	B2, B3, B4	0 = No **21.05%** (32) 1 = Yes **78.29%** (119) . = Missing **0.66%** (1)
	Has researched career advice online before (independent and dependent)	B2, B3, B4	0 = No **53.29%** (81) 1 = Yes **45.39%** (69) . = Missing **1.32%** (2)
	Has researched educational or vocational training courses online before (independent and dependent)	B2, B3, B4	0 = No **18.42%** (28) 1 = Yes **81.58%** (124)
C: Weak ties and career management	Selected at least one weak tie when asked to specify first three contacts that respondent would approach for career-related advice (Independent)	C1, C2, C3	0 = No (all strong) **26.97%** (41) 1 = Yes (some weak) **70.39%** (107) . = Missing 2.63**%** (4)

Table 7.5: Variables operationalised as independent and dependent variables, organised by modal analytical theme. N = 152.

All listed independent and dependent variables are operationalised as binary indicators in analyses. As was the case with the further education student data, a contextual coding policy is applied in these formatting selections. Many indicators employed within this chapter measure whether an event or behaviour has occurred – for example receipt of a form of information from an SNS contact, or having previously used the internet to gain types of career-related information. Respondents are subject to a range of circumstances and constraints with relation to their career management at the time of data collection – from in full-time work to caring for their children full-time. Career management is not necessarily a high priority at this time point. Therefore with reference to these types of indicators, it was judged more suitable to measure whether the event or behaviour had occurred previously, rather than analysing frequencies of occurrence. A relatively small sample size also inhibits meaningful analyses at more granular levels.

Online skill level is a self-assessment of capabilities using the internet measured through how well respondents understood terms which are related to internet use, such as ‘cookies’ or ‘upload’ (survey question 42). Five such terms were supplied, with respondents asked to rate their understanding on a 1-5 point Likert scale. Such a structure naming different terms was operationalised in Hargittai and Hinnant’s (2008) study to assess internet use skill. Different terms were used presently in order to give a modern update to the measure. Respondents who self-rated as fully understanding of all supplied terms (1 on Likert scale) are classed as highly skilled. Other scores are coded as not highly skilled. This indicator is operationalised in order to test for effects of varying degrees of online skill in career management activity and beneficial (informational) outcomes from SNS use, as identified within the research literature (e.g. Rainie and Wellman, 2012).

7.3 Results

A control model serves as a base for analyses predicting the main dependent variable, career positivity. This control model consists of the grouping of control variables described in Table 7.4 (or 'sample characteristics') predicting positivity regarding respondent careers at the time of data collection in a logistic regression model. This serves as a mostly consistent base for further analyses where this dependent variable is operationalised. Independent variables of interest are inserted into the control model to test for influence. Minor variation in control model statistics occurs between analyses because of differences in case numbers within the independent variables.

Control model results provide an opportunity to contextualise this commonly-applied outcome. For example a similar model using further education student data showed results that were inconsistent with well-established employment market trends, leading to the conclusion that some caution should be applied to the interpretation of results stemming from this variable. Table 7.6 shows control model results for career optimism.

DV = Positive about career	Control model
Age	-.08*
Degree education	-.36
Ethnic minority	-.17
Urban	.27
Advantaged inherited background	.20
N =	141
BIC =	211
Psuedo R2 =	.05
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001	

Table 7.6: Career positivity control model. Logistic regression employing sample characteristics (control variables) to predict respondents being positive about their career at the moment. N = 141.

Control model results show one sample characteristic is having a significant impact on career positivity: age. This negative relationship shows that amongst the sample, older mothers of young children are less likely to be positive about their career. As was the case with the further education data control model, these results do not align with established trends seen when employing more conventional indicators of successful career outcomes. For example, degree-level and above education does not have a significant impact, but is a strongly-performing predictor of wage levels in the UK (e.g. Hayward *et al*, 2014; Naylor *et al*, 2015). It should be noted, however, that the sampling frame of female SNS users does not extend to the general population.

7.3.1 Analytical Theme A: Social capital and SNS in career management

The first theme of analyses test for a bonus to the main career outcome (career positivity) stemming from receipt of career-related information via an SNS contact. This is then compared to receipt of such information from a contact, or contacts, through other channels. The contribution of these analyses are twofold; first testing for a social capital-related boost to career management, and second for a benefit of SNS use within hypothesised social capital benefits. Finally in this subsection, the role of online skill is tested with regards to receipt of career-related information via SNS, testing the assumption of the research literature that skill levels effect utility of online tools (e.g. Hargittai and Hsieh, 2010). The second-level digital divide states that any SNS benefits would be stratified by skill.

Table 7.7 details results when receipt of information regarding a job vacancy through SNS (model 1), or by a different mode (model 2) is used to predict career positivity, net of controls. Model 3 operationalises both independent variables net of one another and controls. The analysis finds no effect of instrumental social capital use. When modelled separately neither channel that information regarding a job vacancy is received from has a significant impact on the employment outcome. When tested net of each other, the results are the same, suggesting further that when social capital is operationalised in a job search, use of SNS does not provide an additional bonus.

DV = Positive about career	**Control model**	**A1 (model 1)**	**A1 (Model 2)**	**A1 (model 3)**
Received information from SNS contact – job vacancy		-.70ƚ		-.77
Received information from contact via different mode – job vacancy			-.35	.12
N =	141	141	141	141
BIC =	211	213	215	218
Psuedo R2 =	.05	.07	.05	.07
Key: ƚ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 7.7: Analysis A1. Logistic regressions. Receipt of information from a contact about a job vacancy predicting positivity regarding respondent careers. Information received through SNS (model 1), and through a different mode (model 2) respectively. Model 3 tests independent variables net of each other. N = 141, all net of controls listed in Table 7.4.

Table 7.8 details results of Analysis A2, employing the same format of tests regarding information of a different kind – about an educational or vocational course. Such information is specifically evoked as a career management benefit of SNS use by Rainie and Wellman (2012), notably when describing the case study of 'Linda Evans' (pp. 256-262).

DV = Positive about career	Control model	A2 (model 1)	A2 (Model 2)	A2 (model 3)
Received information from SNS contact – an educational or vocational course		.12		.34
Received information from contact via different mode – an educational or vocational course			-.49	-.63
N =	141	141	141	141
BIC =	211	216	215	219
Psuedo R2 =	.05	.05	.06	.06
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 7.8: Analysis A2. Logistic regressions. Receipt of information from a contact about an educational or vocational course predicting positivity regarding respondent careers. Information received through SNS (model 1), and through a different mode (model 2) respectively. Model 3 tests independent variables net of each other. N = 141, all net of controls listed in Table 7.4.

Regarding information about an educational or vocational course, instrumental social capital use is not found to significantly effect career positivity. Within this instrumental use of social capital, mode of communication is not found to make a difference. Next, Analysis A3 tests whether online skill effects receipt of the forms of information via SNS that were the subjects of A1 and A2. Table 7.9 documents results of these two models, alongside control model statistics. Control models employ sample characteristics predicting each dependent variable.

	Control model: SNS job vacancy information	A3 (model 1, DV = SNS Job vacancy information)	Control model: SNS educational or vocational training course information	A3 (model 2, DV = SNS educational or vocational training course information)
High level of online skill		.68		.59
N =	140	140	140	140
BIC =	212	214	214	217
Psuedo R2 =	.04	.06	.05	.06

Table 7.9: Analysis A3. Logistic regressions. A high level of online skill predicting receipt of job vacancy information via SNS (model 1) and receipt of information relating to an educational or vocational course (model 2), net of respective control models. N = 140.

Results suggest that online skill does not have a significant impact on receipt of either form of potentially beneficial information via an SNS contact. The online skill indicator does not achieve statistical significance in models 1 or 2, and in turn both of these models produce worse model fit than respective control models.

Tests performed within Analytical Theme A do not support hypotheses derived from the research literature. Three findings are produced from results. First, that contrary to perceived benefits of instrumental social capital use within career management (e.g. Lin, 1999), a boost to career positivity is not found. Second, when social capital is used in career management – measured via receipt of relevant information through social networking sites, or through other channels – SNS are not found to make a significant difference to career positivity. This contradicts the assertions of scholars such as Rainie and Wellman (2012). Third, no evidence of a second-level digital divide (Hargittai, 2008a) with regards to receiving beneficial information through SNS is found, as skill level is not found to make a difference.

7.3.2 Analytical Theme B: Online skill and the second-level digital divide

The present section contains interpretation of results within Analytical Theme B (see Table 7.2). It builds upon analyses documented in the previous section, to expand the investigation of the role of the second-level digital divide within career management. Results so far have suggested that SNS ultimately do not benefit respondents' career management, and that technical skills do not in turn play a role in this process. The next results assess what the research literature hypothesises plays a part in the wider question of how beneficial SNS are to career management.

First, determinants of a high level of internet skill are explored. Factors such as education level (e.g. Hargittai and Hinnant, 2008), and age (Prensky, 2001) are found to impact skill levels – higher education level positively, and higher age negatively. Second, internet skill is then operationalised to test whether skill levels impact productive uses of the internet in a career management context (e.g. van Duersen and van Dijk, 2014), as a rebuttal to Rainie and Wellman's (2012) conceptualisation of social networking sites as egalitarian forces in career attainment. A third set of analyses test whether these productive internet uses affect career outcomes, as logic would dictate. Finally productive internet uses are operationalised to predict receipt of beneficial information from an SNS contact, in an expanded investigation of the role of the second-level digital divide. A similar analytical path is followed using Oxford Internet Surveys data (Chapter 4), which identified a skilled online population who utilised the internet productively and also appeared to reap the hypothesised benefits of SNS use. This population was distinct from the general online population, providing evidence of a privileged set of internet users who experienced preferential career outcomes.

DV = High level of online skill	B1 (control model)
Age	.04
Degree education	.39
Ethnic minority	1.22*
Urban	.21
Advantaged inherited background	.34
N =	141
Psuedo R2 =	.06
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001	

Table 7.10: Analysis B1. Logistic regression operationalising control variables to predict a high level of online skill amongst respondents.

Results from analysis B1, exploring determinants of a high level of online skill, are detailed in Table 7.10. Results do not match the picture generated within second-level digital divide literature. One measured sample characteristic is found to significantly impact whether respondents self-rate as highly skilled or not. Those coded as belonging to an ethnic minority (all ethnicities except 'white British') are found to be more likely to be very confident internet users. In the research literature, evidence is found of some (SNS) differential usage by ethnicity (Hargittai, 2008c). However usage of SNS by ethnic minorities found in this study was linked to less favourable outcomes, which in theory are associated with lower skill levels (Hargittai, 2008a). The small number of ethnic minority respondents (19) suggests the result could be an anomaly associated with sample size. No evidence of differential skill levels marked by age or education are found.

Although no evidence of a second-level digital divide affecting internet usage patterns, or associated outcomes, has been found, it is still worthwhile to continue exploring the narrative that the literature review has uncovered relating to the central question of utility of SNS in career management. The next step taken is to employ the high online skill indicator as an independent variable within a set of regression models, predicting three productive uses of the internet separately. These are all career-related and indicate whether respondents have used the internet in these ways before, compared to not having done so; to look for jobs, to research an educational or vocational course, and to gain career advice. Studies focusing on the second-level digital divide find vocational, or productive uses of the internet are predicted positively by skill level (e.g. van Duersen and van Dijk, 2014).

	B2 (model 1, DV = Look online for jobs)	**B2 (model 2, DV = Research educational or vocational course online)**	**B2 (model 3, DV = Research career advice online)**
High level of online skill	.18	.83	-.52
N =	139	140	138
Psuedo R2 =	.01	.04	.06
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 7.11: Analysis B2. Logistic regression models employing high level of online skill as independent variable, predicting use of the internet to; look online for jobs (model 1), research educational or vocational course information online (model 2), and research career advice online (model 3), all net of controls listed in Table 7.4.

Results in Table 7.11 find no effect of online skill on productive, career-related uses of the internet. Whilst being out of step with findings from other research literature, current findings are consistent with the narrative that has developed from analysis of SNS and internet uses of the mothers of young children.

The next set of analyses (B3) tested the relationship between productive internet use and positive career outcomes, as is denoted by research interested in such internet use (e.g. Wei and Hindman, 2011). The three dependent variables operationalised in B2 models 1-3 are employed as independent variables, predicting career optimism amongst respondents. Table 7.12 documents key results.

DV = Career optimism	Control model: Career optimism	B3 (model 1, IV = Look online for jobs)	B3 (model 2, IV = Research educational or vocational course online)	B3 (model 3, IV = Research career advice online)
Independent variable		-.01	.44	.53
Psuedo R2 =	.05	.05	.06	.06
BIC =	208	213	212	212
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 7.12: Analysis B3. Logistic regression models employing use of the internet to; look online for jobs (model 1), research educational or vocational course information online (model 2), and research career advice online (model 3) as independent variables, predicting optimism amongst respondents regarding their careers at the moment, all net of control model. N = 139.

Analysis B3 finds no support for a link between productive internet use in a career management context, and positive career outcomes. The three independent variables employed are not found to significantly effect career optimism, and fit statistics of models 1-3 do not improve on the control model.

The final set of analyses carried out tests for a link between productive internet use and receipt of hypothetically beneficial information from an SNS contact. This link was suggested by results from analysis of Oxford Internet Surveys data, and is also implied through the notion of a second-level digital divide – that potential benefits of career management online are reaped by those with a requisite skill level. Table 7.13 details results from models predicting receipt of information from an SNS contact regarding a job vacancy, net of controls.

DV = Received information from SNS contact regarding job vacancy	B4 (Model 1. IV = Look online for jobs)	B4 (model 2. IV = Research educational or vocational course online)	B4 (model 3. IV = Research career advice online)
Independent variable	1.18*	1.01*	1.06**
N =	142	143	141
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 7.13: Analysis B4, models 1-3. Logistic regression models predicting respondents who had previously received information from an SNS contact regarding a job vacancy. Independent variables; has looked online for jobs before (model 1), has researched information regarding an educational or vocational course online before (model 2), and has researched career advice online before (model 3). Net of control variables listed in Table 7.4.

A link between all three productive internet uses and receipt of potentially beneficial information from an SNS contacts is found. These have a positive relationship with receipt of information from an SNS contact. This implies a link between different productive online behaviours, although this is the first set of analyses to do so.

DV = Received information from SNS contact regarding ed/voc course	**B4 (Model 4. IV = Look online for jobs)**	**B4 (model 5. IV = Research educational or vocational course online)**	**B4 (model 6. IV = Research career advice online)**
Independent variable	.90*	.68	.89*
N =	142	143	141
Key: ˡ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 7.14: Analysis B4, models 4-6. Logistic regression models predicting respondents who had previously received information from an SNS contact regarding an educational or vocational course. Independent variables: has looked online for jobs before (model 4), has researched information regarding an educational or vocational course online before (model 5), and has researched career advice online before (model 6). Net of control variables listed in *Table 7.4*.

Table 7.14 details key statistics of models predicting the second form of information received from an SNS contact; regarding an educational or vocational course. Two of three productive internet usages are found to positively predict receipt of beneficial information from an SNS contact in models 4-6. Therefore, out of six tests, only one significant relationship is identified as not being present – between the two modes of researching information on a course (via an SNS contact and online). The non-significant result perhaps reflects that the variables regard researching this same topic.

The results from Analysis B4 are inconsistent with other findings. Because no evidence is found of a second-level digital divide, or for the benefit of SNS use in career management, it cannot be claimed that the link B4 identifies is suggestive of the existence of a section of internet/SNS users who utilise the internet to reap career management benefits, as asserted by the second-level digital divide.

In summarising the results generated in Analytical Theme B, it cannot be concluded that the existence of a second-level digital divide has been discovered using present data. In particular, the role of online skill was not identified as a linkage between productive internet or SNS use, and career-related outcomes. Identification of positive relationships between productive internet use and receipt of beneficial information through SNS contacts however does suggest that such linkages may be reflective of the narrative derived from the research literature. If this were the case, the indication would be that online skill is poorly measured or operationalised, or both. Given that informational SNS use was not found to influence career-related outcomes, though, a sensible position at this stage would be to accept the null hypotheses with regards to the questions asked of the data to this point. For example, alternative explanations are plausible - results from Analysis B4 could simply represent how diligence in using the internet influences career management – those who look for jobs on job listing websites are more likely to explore other avenues.

7.3.3 Analytical Theme C: Weak ties and career management

The final results section of the chapter explores the efficacy of weak-tie social capital in career management, a unique opportunity enabled by bespoke primary data. This line of enquiry is generated from the common social capital literature assumption that weak ties are more likely to enable access to original information, which allows for opportunity in career management (e.g. Granovetter, 1973; Burt, 2004; Lutter, 2015). Rainie and Wellman (2012) are at the forefront of a group of scholars who have applied the notion of weak ties being beneficial to career outcomes to the digital age, in particular SNS.

A number of analyses are used to test such assertions. First, existence of weak tie contacts within respondent career information networks are tested for a predictive relationship with more favourable career outcomes, via the proxy of career optimism. Second, analyses probe whether those who say they have valuable weak ties within their career information networks are more likely to have received beneficial information through SNS contacts. A positive relationship would imply that SNS are a useful tool for managing weak tie social capital. Finally, the theoretical benefits of weak ties are examined at a more granular level to determine whether they are stratified. Previous research finds that social capital and weak tie social capital effects are unevenly distributed, with the rewards disproportionately in the hands of the already advantaged (e.g. McPherson and Smith-Lovin, 1982; Moerbeek *et al*, 1995; Van Tubergen and Volker, 2015).

Analysis in this section centres around the indicator developed from asking respondents to name the first three contacts (assumed as preferred three, or top three) that they would turn to for career advice, and what their relationship with the contacts was. Identification of relationship allowed for coding into strong or weak ties. Table 7.15 details this coding process.

Strong ties	Weak ties
Partner	Other family member
Close family member	Someone from course
Close friend	Work colleague
	Distant friend/acquaintance
	Friend of a friend
	Tutor/member of staff at college
	Friend of a family member
	Other

Table 7.15: Relationship options provided to respondents when asked who they would turn to for career advice, by strong/weak tie coding typology.

As shown, 'other family members' are treated here as weak, rather than strong, ties. Some studies would consider all family members as strong ties (e.g. Kramarz and Skans, 2014), although this assumes that all relatives are automatically close to the individual. The position taken presently is that this is unlikely to be the case for many, and the two possible descriptions of family members given to respondents ('close' and 'other') are worded to reflect this.

Respondents who named at least one weak tie out of three are classified in analyses as having access to valuable weak tie social capital. Analysis C1 operationalises a binary indicator, coding respondents into a dichotomy in terms of access to valuable weak tie social capital. This independent variable predicts career optimism amongst respondents as dependent variable. Table 7.16 shows results.

DV = Career optimism	Control model: Career optimism	C1 – Valued weak tie(s)
Valued weak ties named		.99*
Psuedo R2 =	.05	.08
BIC =	207	207
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 7.16: Analysis C1. Naming of one weak tie or more in three-person career information networks predicting optimism regarding respondent careers. Model C1 inclusive of controls listed in Table 7.4. N = 138.

Access to valuable weak tie contacts is found to have a significant and positive effect on likelihood of respondent career optimism. The model also explains more variance within the career optimism variable (Pseudo R2 increase), without increasing the BIC value, which would denote a poorer model fit.

Next, a relationship between access to valued weak ties and receipt of potentially beneficial information via an SNS contact is tested for. A significant and positive relationship would suggest that SNS may play a role in the cultivation of this valuable weak-tie social capital. Two types of information received via SNS contacts are operationalised as dependent variables – regarding a job vacancy, and regarding an educational or vocational course. Access to valued weak ties again acts as independent variable. Control model results minus the key independent variables are also provided in Table 7.17 for comparison.

	Control model: Received job vacancy information via SNS	**C2 (model 1, IV = Valued weak tie access)**	**Control model: Received education/vocational training course information via SNS**	**C2 (model 2, IV = Valued weak tie access)**
Independent variable		.05		.22
Psuedo R2 =	.05	.05	.04	.05
BIC =	211	216	215	220
Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 7.17: Analysis C2. Two logistic regression models employing selection of at least one weak tie amongst career information contacts indicator as independent variable, predicting receipt of information via SNS regarding a job vacancy (model 1) and an educational or vocational course (model 2). Each model net of respective control model, which includes variables listed in Table 7.4. N = 140.

Although access to valuable weak ties is found to positively influence respondent career optimism, it is not found to significantly affect receipt of potentially beneficial information via SNS. These combined results suggest that although access to weak ties is beneficial in career management, use of SNS as a mechanism for management of such relationships does not provide a boost to outcomes.

Analysis C3 further interrogates the identified positive relationship between access to valuable weak ties to investigate any stratification of these benefits amongst the sample population. This is achieved by interacting selection of weak ties in career information networks with three variables indicating degree-level or above educational attainment; an advantaged inherited social background; and male CAMSIS scores for respondents based upon current or last jobs. These interactions, together with original indicators, are added to the model produced for Analysis C1 (Table 7.16), to predict career optimism. CAMSIS scores have not been utilised in other analyses presented within this chapter. They indicate social privilege of occupations based upon access to social resources (Lambert, 2018). The three variables are chosen based on research literature precedent. Kramarz and Skans (2014) identify a linear interaction between education and earnings when weak ties are used in gaining employment. Ericksen and Yansey's (1980) study produced similar findings. Moerbeek *et al* (1995) identify a relationship between father's occupation and employment returns when the father is named as a contact that helped respondents secure a job (inherited social background). Although fathers are strong ties, the implications of these results are applied to social capital dynamics generally. Lin and Dumin (1986) identify a 'ceiling effect' on returns from instrumental weak tie use, noting that weak ties become less beneficial the higher up the social hierarchy one resides, as strong ties of elites are likely to be in privileged positions. Table 7.18 records key statistics associated with these models, alongside the model produced for Analysis C1.

	C1 (No interactions)	**C3 (model 1, degree + access to weak ties interaction)**	**C3 (model 2, advantaged inherited social background + access to weak ties interaction)**	**C3 (model 3, CAMSIS scores + access to weak ties interaction)**
Access to weak ties	.99*	.91ᵻ	1.17	-.57
Interaction		.24	-.28	.03
N =	138	138	138	129
Psuedo R2 =	.08	.08	.08	.05
BIC =	207	212	212	220
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 7.18: Analysis C3. Analysis C1 (Table 7.16), with three additional models respectively adding interactions between degree or above educational attainment (model 1), advantaged inherited social background (model 2), male CAMSIS scores based upon respondent current or last jobs (model 3), and access to valuable weak ties. Model 3 also adds male CAMSIS scores indicator.

Results of analysis C3 find no effect for the interactions with access to valuable weak ties amongst respondents. The analyses do not measure weak tie social capital returns when activated, but because they suggest that returns to career outcomes from access to valuable weak ties are not affected by social position or education level, their evidence does not support the findings of previous studies. This evidence should be interpreted with caution, given low respondent numbers r as well as other sample limitations.

Tests within Analytical Theme C produced some results consistent with the research literature, and others not consistent. The majority of literature measures returns from social capital and specifically weak tie use via employment outcomes. This type of direct analysis was not possible with present data. Instead, access to what respondents deemed valuable weak ties in the context of career management is operationalised as an indirect proxy. Using this method, preferential returns to career optimism are found when respondents have at least one valuable weak tie in their career information networks. This evidence supports the notion of weak ties providing better access to opportunity and information in career management (Lin, 1999). Although returns from weak tie and social capital use (e.g. Moerbeek *et* al, 1995; Kramarz and Skans, 2014) are found to be unevenly distributed amongst the population, no evidence is found presently to suggest this.

When the role of SNS is analysed within this equation, it is found that those who have gained potentially beneficial information from ties through SNS are not more likely to have access to valuable weak-ties, refuting the central argument of Rainie and Wellman (2012) that SNS enable users to better produce and maintain valuable weak ties.

7.4 Conclusion

7.4.1 Research Question A: Does SNS use benefit career management?

The analysis within this chapter explores the question of SNS utility in career management directly, by using data on the receipt of beneficial information from SNS contacts as predictors of an employment outcome. This direct analysis finds no additional benefit to career management stemming from SNS use. Doubts over sample quality (a small number of respondents and evidence of bias in response patterns), and over the extent to which career optimism represents success in career management, make a persuasive case for further exploration the question.

Further exploration was achieved by analysing the processes identified which may render SNS as beneficial career management tools. Beneficial employment outcomes associated with instrumental social capital use, and in particular weak tie use (e.g. Granovetter, 1973; Lin, 1999), and the negation of traditional costs of weak tie formation and maintenance afforded by SNS (Rainie and Wellman, 2012) combine to suggest SNS utility in career management. When these individual processes were the subject of analyses, some evidence is found regarding the efficacy of weak tie resources (through respondents having access to valued weak ties). However when SNS are introduced to the equation, no links are established. Therefore some support is found for the notion of weak ties being particularly useful in career management, but use of SNS to manage such relationships is not found to impact this.

When the investigation is broadened further, treating SNS as a section of a wider career management landscape (the internet), a predictive link between productive uses of online non-SNS spaces and SNS is established.

However neither set of productive uses themselves are identified as directly influencing positive (or negative) career-related outcomes.

7.4.2 Research Question B: Who embraces the career-enhancing capacity of SNS?

Although career-enhancing capability of SNS is not established by research presented within this chapter, contrary findings within the research literature and within Chapter 4 results combined with present sample limitations render a case for exploring who embraces SNS use in career management.

Only limited evidence is found in support of the existence of a second-level digital divide affecting career management returns from SNS use within this chapter. The main mediating attribute between productive SNS and wider internet use and users, skill level, identified by Hargittai (2008a), is not found to shape uses or associated outcomes. Further, skill level is not found to be a reflection of the structural factors that shape offline inequalities, such as how educated an individual is (van Duersen and van Dijk, 2014).

The limited evidence found in support of the existence of the second-level digital divide in the form asserted by key authors in the area comes in a positive relationship between productive internet use and productive SNS use. This relationship infers the existence of a population of internet users who utilise the productive capacities of the internet, although the career management benefits of such use are not established.

Finally although evidence of the efficacy of weak ties within career management is found presently, evidence of an uneven distribution of these effects – again viewed within the research literature as ultimately explained by structural factors such as social class (e.g. Borlagdan, 2015) – is not found.

Chapter 8: Redundancy and re-entry into employment

8.1 Introduction

Chapter 8 is based upon analysis of primary data collected from respondents who had been made redundant from their job within the last three years (at the time of data collection). The primary focus of this case study is similar to that presented in Chapter 5; how useful are SNS as a career management tool in exiting unemployment? Chapter 5 is based upon secondary data of relatively limited scope with regards behavioural (e.g. how people use SNS) and social network composition (e.g. differentiation between weak and strong ties) variables. That data was however rich in variables measuring employment outcomes that were used as dependent variables in tests measuring effects of SNS use. Chapter 8 data, and the accompanying analytical strategy, is of a different character; a smaller sample universe, one measurement representing a successful employment outcome, a greater range of behavioural and social network composition indicators employed. This design ensures that this sub-topic of employment or career management research – exiting unemployment – is addressed in relatively comprehensive fashion. Chapter 5 analyses are particularly strong in testing the value of SNS in relation to employment outcomes, but weaker in exploring nuances surrounding SNS use. Chapter 8 places more emphasis on these nuances, at the expense of covering a diversity of employment outcomes.

8.1.1 Literature overview

Social capital is identified as a form of capital in its own right, which interacts with other forms, such as cultural capital (Bourdieu, 1986). It is instrumental in career management as an unlocking mechanism that can lead to information critical to gaining new positions (Granovetter, 1974; Lin, 1999), greater compensation in roles (Burt, 2004), and decreased likelihood of early exit from employment (Bonoli and Turtschi, 2015). SNS are viewed by some influential commentators as modern enablers of equality of opportunity, through the reduction of costs traditionally inhibitive to the development and maintenance of a diverse network of loosely-knit ties (Rainie and Wellman, 2012).

Previous research finds an association between the closeness of relationships and the utility of information received, in context of career management. Weaker ties, such as acquaintances, provide more useful information than closer relations (Lin and Dumin, 1986). Further, informational benefits associated with weaker ties are not uniform across the population. Characteristics such as gender (McPherson and Smith-Lovin, 1982), ethnicity (Green *et al*, 1995), and educational attainment (Ericksen and Yansey, 1980) have been identified as markers of differential levels of social capital, and/or effects from instrumental use.

In opposition to Rainie and Wellman, other scholars believe the opportunity-equalising benefits of SNS and wider internet space are over-hyped. As in the physical world, structural circumstances inhibit the ability of internet users to unlock potential benefits. As such, the ‘second-level digital divide’ (Hargittai, 2008a) considers a spectrum of differentiated usages and outcomes associated with the proportion of the population that has access to the internet.

Further literature explores the consequences of unemployment spells, and barriers to job market re-entry. Unintended unemployment can have serious consequences for wellbeing (McKee-Ryan *et al*, 2005). Feeling isolated can be a consequence (Gallie *et al*, 2003), of which the loss of supportive social networks is a cause (Morris and Irwin, 1992). Males in particular who have well-developed social capital are more likely to be recruited through informal channels post-redundancy (Morris, 1985). Such recruitment methods are more frequent in times of recession (Morris, 1984). Morris also found that weak ties were not as effective during times of financial hardship (i.e. unemployment) as mixing across social groups was less likely – a barrier identified by Rainie and Wellman (2012) as mitigated by SNS use. Unemployed social media users feel less insecure and excluded than non-users (Fuels *et al*, 2014).

8.1.2 Research questions addressed

This sub-section provides an overview of how analyses presented later in the chapter relate to Thesis research questions. Research questions are provided for reference in Table 8.1.

Research Question A: Does SNS use benefit career management?	**Research Question B: Who embraces the career-enhancing capacity of SNS?**
A1) How important is social capital in the contemporary employment market?	**B1)** Is there evidence of a second-level digital divide amongst SNS users?
A2) Are any benefits a result of SNS' facilitation of weak tie network management?	**B2)** Who uses the internet to enhance human capital?
A3) How important is the online world in CMS strategy in comparison to traditionally offline methods?	**B3)** Is there an uneven distribution of positive, career-outcome effects from weak tie social capital use?

Table 8.1: Thesis research questions.

Analyses presented are detailed in relation to which research questions they address in Table 8.2. Analyses are categorised into three analytical themes; SNS use and online skill, social support and unemployment, and weak ties and career management. Although the categorisations are not absolute (all analyses are related directly or indirectly to SNS use, for example), the analytical themes provide order and reference points for results, and capture the general context of analyses within.

Analytical theme	Analysis question	Modelling strategy	Research question(s) addressed
A: SNS use and online skill	**(A1)** Does SNS use provide a bonus to likelihood of re-employment? What other factors affect it?	1 model: Control model gauging factors predicting re-employment following redundancy, including absolute SNS use	Research Questions A1-3
	(A2) Does receipt of information through contacts boost chances of re-employment?	4 models: Receipt of information regarding job vacancies and an educational or vocational training course from a contact predicting re-employment. Receipt through SNS (2 models) and other channels (2 models)	Research Questions A1, A3
	(A3) Does online skill level effect receipt of information through SNS?	2 models: Self-rated online skill level predicting receipt of two forms of information through SNS	Research Question B1
B: Social support and unemployment	**(B1)** What barriers, including lack of social support, affect re-employment?	3 models: Social support, isolation and lack of routine predicting re-employment	Research Question A1
	(B2) Do factors in B1 affect receipt of potentially beneficial career management information?	6 models: Receipt of information relating to job vacancies (3 models) and educational or vocational training (3 models) from contacts via SNS and/or other channels predicted by social support, isolation, lack of routine	Research Question A1, B
	(C1) Are weak tie career information resources	1 model: Naming of 1 weak tie or more within top 3 career information contacts predicting re-employment	Research Question A2 (in

	associated with better employment outcomes?		conjunction with analysis C2)
C: Weak ties and career management	**(C2)** Are respondents with more valuable weak tie resources more likely to receive career-related information via SNS?	2 models: Naming of 1 weak tie or more within top 3 career information contacts predicting receipt of 2 forms of career information via SNS	Research Question A2 (following from Analysis C1)
	(C3) Are the effects of weak tie social capital unevenly distributed?	4 models: C2 repeated four times, each model featuring an additional interaction between selection of weak ties in top 3 career information contacts and being a woman, degree attainment, high inherited social status, male CAMSIS scores respectively	Research Question B3

Table 8.2: Analytical structure details and research questions addressed.

Sets of, and individual analyses are further described in respective results sections. Collectively analyses address all project research questions, with the exception of Research Question B2. This question is not addressed within this chapter as it is explored in depth elsewhere.

8.2 Sample characteristics

Data was collected from 156 respondents who had been made redundant from employment within the previous 3 years. Respondents were identified through having engaged with the Skills Development Scotland (SDS) redundancy support programme, Partnership Action for Continuing Employment (PACE (SDS, N. D.)). SDS acted as gatekeeper in forwarding on a survey advertisement containing a survey link to stakeholders via email. Therefore, all respondents are internet users. Country or area of residence within the UK is not measured, as it is assumed that all respondents are Scottish residents based upon their engagement with SDS.

A range of PACE support services were accessed by respondents. For example 50% had received information on funding for training, and 47% of respondents help with CV's, applications and cover letters. The research took place at a time that the North Sea oil and gas industry was in decline. Around 150,000 UK oil and gas industry jobs were lost between 2014 and 2017 (BBC, 2017). As a result, the sample contains a noticeable amount of individuals who were made redundant from this sector. Sample proportion is difficult to quantify because not all respondents specifically named the sector that they worked in when asked (occupations instead coded on generic job title information, e.g. ‘customer service assistant’). 46% explicitly stated that they worked in the offshore oil and gas industry, or for connected organisations (e.g. drilling equipment manufacturers). This sampling quirk should therefore be taken into account when interpreting results. 13% of respondents had secured employment since being made redundant that required them to undertake further training qualifications at the time of the survey, hinting at a change of industry. Overall 65% had secured employment since being made redundant. For 35% of respondents, redundancy from employment has been experienced more than once.

Other sample characteristics are operationalised as control variables in most multivariate analyses. Frequencies are displayed in Table 8.3.

Variable description (coding detail if different in analyses)	**Category**	**% of sample (freq.)**	**% of valid sample (if some data missing)**
Gender	Female	30.13% (47)	30.32%
	Male	69.23% (108)	69.68%
	Missing data	0.64% (1)	
Highest educational attainment (dummy binary variable indicating degree or higher attainment in analyses)	Degree or higher	33.97% (53)	
	Post-secondary	38.46% (60)	
	Compulsory secondary	27.56% (43)	
Ethnicity (not operationalised in analyses)	White UK	92.95% (145)	95.39%
	White other	1.28% (2)	1.32%
	Asian	1.28% (2)	1.32%
	Black African	1.28% (2)	1.32%
	Black Caribbean	0.64% (1)	0.68%
	Missing data	2.56% (4)	
Parent with a degree: Inherited social advantage	Yes	14.10% (22)	
	No	85.90% (134)	
Urban density	Urban	55.77% (87)	
	Rural	44.23% (69)	

High level of online skill	Yes	37.82% (59)	38.83%
	No	59.62% (93)	61.18%
	Missing	2.56% (4)	
SNS user	Yes	87.18% (136)	
	No	12.82% (20)	
Time since made redundant	Within 3 months	12.82% (20)	12.90%
	3-6 months ago	9.62% (15)	9.68%
	6-12 months ago	19.23% (30)	19.35%
	1-2 years ago	40.38% (63)	40.65%
	2-3 years ago	17.31% (27)	17.42%
	Missing data	0.64% (1)	
Age: Mean = 48.58 | Std. Dev. = 10.64 | Range = 26-68 | Skewness = -.64 Missing = 1.92% (3)			
Male CAMSIS score: Mean = 45.26 | Std. Dev. = 16.45 | Range = 8.76-80.43 | Skewness = .31 Missing = 0.64% (1)			

Table 8.3: Sample characteristics. Variables mainly operationalised as controls in multivariate analyses. N = 156.

The sample is mostly male (70%), which differs from other primary data collected. The mothers sample (Chapter 7) is 100% female, and women (55%) slightly outnumber men in the further education student sample. Gender is controlled for in all multivariate analyses primarily because research shows women have less access to theoretically beneficial weak ties (Lutter, 2015). Women are also less likely to cultivate weak ties via SNS (Mazman and Usluel, 2011).

Average sample age is 49 years old, with respondents ranging from 26 to 68 years. These statistics show that of primary sample data collected, this sample is the oldest at the aggregate level. Respondents from this case study therefore represent a population at quite an advanced stage of their working lives, which compliments snapshots of earlier stages recorded by the other case studies. Online skill is operationalised as both a control variable, and as more focal point in some analyses because of its central role within the second-level digital divide. This indicator is based upon a measurement designed by Hargittai and Hinnant (2008), and is coded consistently with indicators used in further education student and mothers of young children data. 34% are classified as having a high level of internet skill. This proportion is higher than found amongst other primary samples which belong to a younger aggregate age grouping. This is surprising given the implications of the theory of 'digital natives' (Prensky, 2001), that younger generations whose formative years are characterised by ubiquitous connected technologies should be more competent users.

Educational attainment is controlled for in analyses because it is a key marker of differential outcomes in respect of all analytical themes. For example it best predicts wage levels (an indicator of job quality) in the UK (Howard *et al*, 2014), and informational use of the internet (Wei and Hindman, 2011). 34% of respondents have attained a degree-level educational qualification or higher. This figure is much lower than that of the mothers' sample (66%), which was calculated to over-represent well-educated individuals. Although lower, the present figure is still higher than that recorded for the Scottish population by the 2011 census, 26% (National Records of Scotland, 2016).

Although a marker of differential return from instrumental use of social capital (Elliot, 1999), ethnicity is not operationalised as a control variable in analyses. 95% of valid respondents identify as white British. As a result, too few cases remain for even a reductive indicator (e.g. binary white British/other) to function in statistical analysis. This sample under-represents individuals of non-white British background in Scotland, who total 8% of the population (NRS, 2018a).

A measure of inherited position within the social hierarchy is included in analyses, consistent with other primary analysis strategies. As with those data, missing cases (22) are imputed into the non-advantaged category because it is assumed that respondents would know if a parent had attended university. The other two options for parental educational attainment given within the survey – compulsory secondary and further (non-degree) education – are deemed the source of respondent uncertainty that likely produced non-responses. 14% of respondents have one or more parents that attended university and are coded as having inherited an advantaged position. This proportion is much lower than that of the mothers sample (38%) and the further education student sample (32%). It is difficult to determine wider population representativeness, as statistics for parental pairs do not exist. The relatively low figure compared to other project samples is unlikely to be explained by a post-1992 UK higher education expansion (Tomlinson, 2008) cohort effect, because 1992 is relatively recent in generational terms. The sample is therefore tentatively described as over-representative of individuals born into a working-class background. This control is included on the basis of an identified positive relationship between father's occupational status and employment returns when social capital is used to gain employment (Moerbeek *et al*, 1995), although some other studies find this relationship does not continue beyond respondents' first job (Lin *et al*, 1981).

Urban density should theoretically be a mediating factor in positive employment outcomes from use of the internet, due to slower rural broadband speeds in the UK (Ofcom, 2018b). Autonomy of use is identified as a predictive factor of productive internet use (Hargittai and Hinnant, 2008). 44% of the sample are classified as resident in a rural area, which suggests over-representation when compared with the actual population proportion, 17% (Scottish Government, 2018). Broadly similar levels of over-representation have occurred in other primary samples collected, suggesting that at least some of this difference is likely down to measurement error.

Male CAMSIS scores indicate social privilege of occupations based upon access to social resources (Lambert, 2018), and act as a control for job quality in an analytical strategy that utilises an indicator of getting a job as the main outcome. These scores are based upon jobs that respondents were made redundant from. A large range of scores (9-80) denote a great range of occupational prestige within these jobs. This prestige loosely correlates with more widely utilised stratification measures such as NS-SEC (ONS, N. D.(b)), and therefore the scores represent a diverse range of occupational skill levels.

Time since made redundant is also controlled for in relevant analyses. This is because many operationalise as dependent variable the gaining of employment following being made redundant (or re-employment). The amount of time that has passed inevitably affects chances of gaining re-employment, as those recently made redundant may be only just beginning their job searches.

Absolute SNS use, like online skill, is employed both as a control and variable of particular interest in analyses. It is most commonly used as a control variable, as analyses testing effects of SNS use place more emphasis on how the platforms are being used. 87% of the sample are SNS users, which is greater than the average UK figure of 67% in 2019 (Battisby, 2019). Over-representation is implicit in the research design through delivery of the survey online. This is deemed appropriate in relation to the second-level digital divide.

8.2.1 Independent and dependent indicators

This sub-section details variables employed in analyses as of particular interest. This categorisation is not definitive. Labelling variables as controls or an independent/dependent indicator is based upon mode. For example the online skill variable detailed previously is utilised as an independent/dependent factor, but more often as a control.

Independent/dependent variables are detailed in Table 8.4, categorised by modal analytical themes detailed in Table 8.2. As previously mentioned, the main outcome utilised is a binary measure of whether respondents are employed at the time of data collection, following being made redundant within the last three years. This measure is designed to definitively capture first employment gained following redundancy. It is discussed in greater detail in Chapter 3.4.4.3. 65% of respondents are re-employed at the time of data collection. All are assumed as active jobseekers based upon their interaction with SDS. This outcome does not account for responses to unemployment that are not immediate job seeking, and this should be factored in to result interpretation. For example, some respondents may choose to study a degree instead. If they are not in paid work alongside study, such respondents would be classified as not having exited unemployment.

Analytical theme	Variable information (Operationalisation)	Analyses used in	Frequencies and structure
Main dependent variable	Has gained re-employment (dependent)	A1, A2, B1,C1	0 = No **35.26%** (55) 1 = Yes **64.74%** (101)
A: SNS use and online skill	Has received information from an SNS contact regarding a job vacancy (independent and dependent)	A2, A3, C2, C3	0 = No **29.49%** (46) 1 = Yes **68.59%** (107) . = Missing **1.92%** (3)
	Has received information from an SNS contact regarding a vocational or educational course (independent and dependent)	A3, C2, C3	0 = No **29.49%** (46) 1 = Yes **68.59%** (107) . = Missing **1.92%** (3)
	Has received information from a contact regarding a job, not through SNS (independent)	A2	0 = No **15.38%** (24) 1 = Yes **82.69%** (129) . = Missing **1.92%** (3)
B: Social support and unemployment	Had adequate social support after being made redundant (independent)	B1, B2	0 = No **67.95%** (106) 1 = Yes **31.41%** (49) . = Missing **0.64%** (1)
	Struggled to maintain a daily routine after being made redundant (independent)	B1, B2	0 = No **51.28%** (80) 1 = Yes **48.08%** (75) . = Missing **0.64%** (1)
	Felt isolated after being made redundant (independent)	B1, B2	0 = No **43.59%** (68) 1 = Yes **55.13%** (86) . = Missing **1.28%** (2)
	Has received information from a contact regarding a job vacancy before **via any channel** (independent)	B2	0 = No **12.82%** (20) 1 = Yes **85.90%** (134) . = Missing **1.28%** (2)
	Has received information from a contact regarding an educational or vocational training course before **via any channel** (independent)	B2	0 = No **9.62%** (15) 1 = Yes **89.10%** (139) . = Missing **1.28%** (2)

C: Weak ties and career management	Selected at least one weak tie when asked to specify first three contacts that respondent would approach for career-related advice (Independent)	C1, C2, C3	0 = No (all strong) **16.67%** (26) 1 = Yes (some weak) **81.41%** (127) . = Missing **1.92%** (3)

Table 8.4: Independent and dependent variables, organised by modal analytical theme. N = 156.

All listed independent and dependent variables are operationalised as binary indicators in analyses. As was the case with further education student data, a contextual coding policy is applied in these formatting selections. Many indicators employed within this chapter measure whether an event or behaviour has occurred – for example receipt of a form of information from an SNS contact. Collection of data containing additional granularity – such as associating particular instances of receipt of advice with gaining a job – was deemed too demanding on respondents. The relatively small sample size also rendered binary indicators more suitable, as additional categories may not have the response weight to function adequately in statistical analysis.

Data bespoke to each primary sample was collected, although not always utilised in final presentations of results. In this chapter, the opportunity to present results from particularly novel data is taken through tests involving three indicators in context of how respondents felt following redundancy; whether they had enough social support, whether they struggled to maintain a daily routine, and whether they felt isolated. These are identified barriers to re-employment within research literature (Morris and Irwin, 1992; Gallie *et* al, 2003). Another underlying factor behind this choice was similarity of results with the mothers' chapter (Chapter 7) when replicating analytical structure. These unreported results are referred to in the chapter conclusion (8.4).

8.3 Results

In common with previous chapters based upon analysis of primary data, a 'main' outcome is identified representing a successful career outcome. Choice of main outcome presently – whether a respondent has successfully gained employment after being made redundant – is reflective of the overall theme of the chapter; the role of SNS in exiting unemployment. Table 8.5 details results of a control model operationalising re-employment as dependent variable predicted by variables most often employed as controls accounting for mediation within the tested relationship between dependent and independent variables. The control model serves two functions. First, it enables a comparison between significant factors found to affect employment outcomes in the literature and using present data. Second, effects from factors of particular interest with regards project research questions on gaining re-employment are tested, ahead of being explored in greater detail in subsequent analyses.

DV = Gained re-employment		Control model
Age		-.03
Degree education		-.36
Female		.26
Urban		.06
Advantaged inherited background		-.57
CAMSIS		-.04**
Online skill - high		.03
SNS user		.58
Time since made redundant:	<3 months	-2.35**
	3-6 months	-1.54*
	6-12 months	-1.13ᵻ
	1-2 years	-.95
BIC =		233
Psuedo R2 =		.12
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 8.5: Re-employment control model (Analysis A1). Logistic regression employing sample characteristics (control variables) to predict respondents gaining employment following being made redundant. Time since made redundant reference category = 2-3 years. N = 146.

Two factors are found to have a significant influence on respondents gaining employment. Time since made redundant, as predicted, has a linear effect. Compared to the base category of being made redundant 2-3 years ago, those made redundant more recently are less likely to be re-employed. CAMSIS scores have a significant and negative effect, meaning that higher ranked occupations take longer to attain. Or, alternatively it is easier to gain employment in less prestigious occupations. Net of these significant factors, no others are found to affect re-employment. This is perhaps unsurprising, as some factors may simply affect job quality, rather than attainment. For example, we know that having a degree significantly predicts job quality when measured via proxies such as earnings (Hayward *et al*, 2014).

Factors not found to have a significant impact also include SNS use and online skill, which should make a positive difference according to the findings of the literature review. SNS use should enable people to better manage their weak ties (Rainie and Wellman, 2012), and therefore be more likely to be in a position to receive advantageous career management information. In turn online skill should affect ability to use SNS effectively, as per the second-level digital divide (Hargittai, 2008a). The next section presents further results from analyses within Analytical Theme A.

8.3.1 Analytical Theme A: SNS use and online skill

Other results from analyses listed in Table 8.2 under ‘Analytical Theme A’ are discussed in this section. Although the control model (Analysis A1) shown in Table 8.5 does not indicate that either SNS use or online skill significantly influence respondent exits from unemployment, results within this section give a much fuller account.

First, receipt of potentially valuable information via SNS is tested for influence on gaining re-employment (Analysis A2). This test progresses beyond simply assessing whether having an SNS profile helps within career management to include indicators on usage types. These models are compared to similar models employing receipt of information through channels other than SNS. In addition to exploring the utility of SNS, the hypothesised career management benefits of social capital use (Lin, 1999) are addressed.

The second set of models (Analysis A3) presented within this section test for influence of online skill level on receipt of potentially beneficial information via SNS contacts. According to the second-level digital divide (Hargittai, 2008a), it is internet users of higher skill levels who have the ability to use the internet productively. Those without requisite skill therefore, are hypothetically less likely to be in receipt of such potentially beneficial information.

Analysis A2 consists of three regression models predicting re-employment, net of controls listed in Table 8.5. Model 1 employs receipt of information through an SNS contact regarding a job vacancy as an independent variable, and Model 2 the same information through a different channel. Model 3 uses both indicators as independent variable, to test for SNS utility within social capital use. Because SNS use is controlled for, the minority sample element who do not use SNS are included within the analyses. Key statistics from the control model (Analysis A1) are included for reference with A2 key statistics in Table 8.6.

DV = Gained re-employment	Control model	A2 (model 1)	A2 (Model 2)	A2 (model 3)
Received information from SNS contact – job vacancy		-.07		.31
Received information from contact via different mode – job vacancy			.20	-.17
BIC =	214	219	219	224
Psuedo R2 =	.11	.11	.11	.11
Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 8.6: Analysis A2. Logistic regressions. Receipt of information from a contact about a job vacancy predicting respondents becoming re-employed. Information received through SNS (model 1), and through a different mode (model 2) respectively. Model 3 tests independent variables net of each other. N = 142, all net of controls listed in Table 8.5.

Receipt of information from a contact regarding a job vacancy does not produce a significant effect on gaining re-employment in Analysis A2. In summary of Analysis A2, indicators representing instrumental use of social capital, as well as specific use through the medium of social media, are not found to influence the employment outcome.

Analysis A3 tests whether receipt of the two forms of information through SNS is affected by respondent online skill levels. Key statistics from two control models (each predicting dependent variables minus inclusion of the independent variable) are included with results of the test in Table 8.7. Receipt of the two forms of information are not operationalised in a model together because effects net of each other are not the subject of the test. Time since made redundant and CAMSIS indicators are removed from the control model as a result of alternative dependent variable operationalisation.

	Control model – educational/vocational course information	A3 (model 1)	Control model – job vacancy information	A3 (Model 2)
Online skill level: High		.22		-.09
BIC =	205	210	198	203
Psuedo R2 =	.04	.04	.07	.07
	Key: ᶧ p<0.1 * p<0.05 ** p<0.01 *** p<0.001			

Table 8.7: Analysis A3. Logistic regressions. Receipt of information from a contact about an educational or vocational training course (model 1), and a job vacancy (model 2) via SNS predicting respondents becoming re-employed. Control variables included: female, age, SNS use, urban density (urban), advantaged inherited background, degree or above educational attainment. N = 144.

Receipt of both forms of information through an SNS contact is not found to be predicted by respondent online skill level. Therefore no element of a second-level digital divide is found to operate within productive SNS use.

Results generated by tests within Analytical Theme A find no evidence of hypothesised effects of instrumental social capital use, SNS as a medium for such use, and online skill as a barrier toward benefitting from effects. For respondents made redundant from employment within the last 3 years, gaining re-employment is not affected by any of these factors. Sample limitations cannot be disregarded – for example the relatively low case numbers – in generation of the null hypothesis, although other significant effects found in construction of the control model predicting re-employment (time since made redundant and CAMSIS scores), suggest lack of statistical power is not necessarily a defining characteristic of the data.

8.3.2 Analytical Theme B: Social support and unemployment

Up to this point, the analytical narrative has followed an identical structure to that presented within Chapter 7, with similar results achieved. In Chapter 7, no boost to career management was found to occur stemming from instrumental social capital use, productive SNS use, or evidence of mitigating second-level digital divide processes within the first set of results presented (7.3.1). These factors were then explored further in a thorough investigation of hypothesised benefits of SNS use. Because of result similarity and the availability of other types of bespoke indicators, it was deemed more worthwhile to explore different questions within this chapter. The analytical strategy of Chapter 7 is returned to in the next section, in analysing the efficacy of weak ties in career management. This section, however, explores factors identified within the research literature that act as a drag on exiting unemployment. Social resources receive particular attention, in accordance with project research questions.

Results from two tests are presented (Analytical Theme B). Both tests involve operationalisation of three indicators identified within the literature as being specific consequences of exiting employment. These measure the extent to which respondents felt they had people around them from whom they could seek advice and support (social support), extent to which they struggled to maintain a daily routine (motivation), and extent to which they felt isolated (isolation). Social support and isolation indicators are perhaps superficially similar, although measure different things. Lack of social support may be a symptom of isolation, but the two do not necessarily correlate. A respondent may not feel isolated as a result of social interaction, but the subjects of those interactions may not have worthwhile assistance to offer. Those with access to social support are more likely to be recruited via informal channels post-redundancy (Morris, 1984), a recruitment method particularly prevalent in times of recession (Morris, 1985). As noted when contextualising sample properties, a good proportion of respondents are likely effected by a recession within the offshore UK oil and gas industry. A spell of unemployment has an adverse impact on daily routine maintenance, which in turn distances the individual from others (Morris and Irwin, 1992). Feeling isolated also occurs commonly during spells of unemployment (Gallie *et al*, 2003).

All indicators are originally measured using a 5-point Likert scale, and reduced to binary variables indicating affirmative response versus non-affirmative response. Analysis B1 explores the effects of identified factors on likelihood of gaining re-employment, and B2 subsequently tests the extent to which the factors influence receipt of potentially valuable information from contacts. The latter (B2) explores the ways in which redundancy consequences further impact career management.

Table 8.8 provides key results of Analysis B1. Key statistics from the control model predicting re-employment (as per Table 8.5) are provided for comparison alongside the three regression models. Each model respectively employs one of the above described indicators as independent variable predicting re-employment of respondents, net of the control model.

DV = Gained re-employment	Control model	B1 (model 1)	B1 (Model 2)	B1 (model 3)
Had access to social support		.16		
Struggled to maintain daily routine			-.10	
Felt isolated				-.20
BIC =	217	222	222	222
Psuedo R2 =	.11	.11	.11	.11
Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 8.8: Analysis B1. Logistic regressions. Unemployment factors predicting becoming re-employed. Unemployment factors: respondents felt they had access to social support (model 1), respondents struggled to maintain a daily routine (model 2), respondents felt isolated (model 3). N = 144, all net of controls listed in Table 8.5.

Levels of social support, daily routine maintenance and isolation are not found to significantly influence the probability of respondents exiting unemployment, net of controlling factors. Addition of these indicators to the control model predicting re-employment also produces worse model fit statistics. Although the indicators related to consequences of unemployment are not directly found to influence employment outcomes, theory still suggests that they should affect receipt of potentially useful information from SNS contacts. This logic is formed on the basis that two indicators measure lack of, or decline of, social capital (social support, isolation). The other indicator describes dislocation with experience of wider society, and therefore is also related to social capital.

Analysis B2 tests this logic, employing each indicator as an independent variable respectively in three regression models where previous receipt of any form of useful information via SNS (regarding job vacancies and/or educational or vocational training courses) is employed as the dependent variable. Control model statistics (unrelated controls removed) are also provided for reference in Table 8.9.

DV = Receipt of potentially useful career management information via SNS	Control model	B2 (model 1)	B2 (Model 2)	B2 (model 3)
Had access to social support		1.98ᵻ		
Struggled to maintain daily routine			.76	
Felt isolated				1.86*
BIC =	122	122	125	119
Psuedo R2 =	.11	.16	.12	.20

Key: ᵻ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 8.9: Analysis B2. Logistic regressions. Unemployment factors predicting previous receipt of potentially useful information via an SNS contact (regarding job vacancies and/or an educational or vocational course. Unemployment factors: respondents felt they had access to social support (model 1), respondents struggled to maintain a daily routine (model 2), respondents felt isolated (model 3). N = 145. All net of following controls; female, age, SNS use, urban density (urban), advantaged inherited background, degree or above educational attainment, high internet skill.

Results find some support for influence of unemployment factors on receipt of potentially valuable information via SNS. Contrary to expectations, respondents who felt isolated following being made redundant are significantly more likely to have received information potentially beneficial to career management before via SNS. Model 3 fit statistics are also improved, with the pseudo squared value almost doubling, suggesting that the inclusion of this explanatory factor helps the model explain a good portion of variance within the dependent variable. Indicators relating to maintenance of daily routine and access to social support are not found to have significant effects, although the coefficient estimate for access to social support is approaching significance. Further, access to social support improves model fit statistics compared to the control, suggesting that sample size could be inhibiting the coefficient from becoming statistically significant.

Contextual logic may help explain the unexpected positive effect of isolation on receipt of information via SNS. The measurement of receipt of information via SNS is not limited to respondent redundancy spells. Therefore, isolation and receipt of information may not coincide, and perhaps isolation is a relative concept, whereby individuals with generally higher levels of social capital are more likely to notice a reduction in social contact with others. Nonetheless, no support is found for an effect of higher levels of social support on likelihood of receiving potentially beneficial information via SNS.

In summary of results generated within Analytical Theme B, no evidence is found in support of findings from the research literature. Although Lack of access to social support, loss of a daily routine and isolation are perceived as negative consequences of unemployment spells (Morris, 1984; Morris and Irwin, 1992; Gallie *et al*, 2003) and indicate decline in social capital viewed as beneficial within career management (Lin, 1999). Of statistically significant evidence, limited support for a reversed hypothesis is found, on the face of it. Those who felt isolated following being made redundant are more likely to have received potentially beneficial information from contacts via SNS previously. Literature precedent and reasonable logic suggest that this finding is perhaps a result of contextual factors, rather than a specific positive relationship between isolation and social capital via SNS.

Another interpretation of the significant, positive effect of isolation on likelihood of receiving potentially valuable information via SNS can be made, which perhaps sheds light on this background context. Isolation could be felt in response to a loss of a community of work colleagues (which may be particularly true of offshore oil and gas workers, given this mode of work is atypical – workers spend evenings with colleagues, rather than returning home to a family). Such respondents may be more likely to communicate with the lost community via SNS, and thus be more likely to hear about opportunities. Nonetheless, hearing about these job opportunities is not found to significantly increase likelihood of getting a job, as per results of Analysis A2.

8.3.3 Analytical Theme C: Weak ties and career management

This final results section is based upon analyses that test hypothesised benefits to career management from utilisation of weak tie social capital. This line of enquiry is generated from the common social capital literature assumption that weak ties are more likely to enable access to original information, which allows for opportunity in career management (e.g. Granovetter, 1973; Burt, 2004; Lutter, 2015). Rainie and Wellman (2012) are at the forefront of a group of scholars who have applied the notion of weak ties being beneficial to career outcomes to the digital age, in particular within context of SNS use. SNS are viewed as a tool which unlocks efficient social capital management for a much wider range of people by removing traditional barriers inhibitive to development and maintenance of a varied portfolio of weak ties.

The opportunity to conduct such analyses is made possible through collection of data where contacts named by respondents as being their most important social resources of career-related information are classified as strong and weak ties. Table 8.10 details the coding process whereby ties are classified as strong or weak.

Strong ties	Weak ties
Partner	Other family member
Close family member	Someone from course
Close friend	Work colleague
	Distant friend/acquaintance
	Friend of a friend
	Tutor/member of staff at college
	Friend of a family member
	Other

Table 8.10: Relationship options provided to respondents when asked who they would turn to for career advice, by strong/weak tie coding typology.

Respondents are asked to classify their top three career-related information contacts into one of the relationship categories. These are then coded by the Researcher into strong and weak ties. The indicator operationalised is a binary variable denoting the presence of weak ties within the three contacts mentioned, versus a choice of three strong ties. Over-reliance upon strong ties to gain information related to career management is in theory a disadvantage, as strong ties - or bonding social capital - is associated more with emotional rather than informational benefits (Putnam, 2000). Although a caveat to this is the ‘ceiling effect’ of weak ties (Lin and Dumin, 1986), whereby strong ties of those at the top of the social hierarchy are likely to be as, or more, effective in informational terms than weak ties.

Analyses C1-C3 involve use of this data. Analysis C1 directly tests for impact of weak tie access in career information networks on respondent likelihood of exiting unemployment. Analysis C2 also employs the weak tie access indicator as independent variable, predicting receipt of potentially valuable information from an SNS contact. Finally Analysis C3 tests for stratification of weak tie effects by repeating analysis C1 and adding interactions between access to weak ties and stratification indicators.

Table 8.11 details key statistics relating to Analysis C1. A control model predicting re-employment is included for reference.

DV = Gained re-employment	Control model	C1 (model 1)
Access to weak ties		-.77
BIC =	212	215
Psuedo R2 =	.12	.13
Key: ᵗ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table 8.11: Analysis C1. Logistic regression. Naming of at least 1 weak tie in 3-contact career information network predicting becoming re-employed. N = 143. All net of controls listed in Table 8.5.

No significant effect of access to weak ties within career information networks is found on likelihood of exiting unemployment, suggesting that the effectiveness of information received from contacts via SNS does not differ by tie type. Results presented earlier also suggested that social capital use in general does not significantly affect re-employment.

Key results from analysis C2 are listed in Table 8.12. These results are from two models which operationalise each indicator of receipt of potentially valuable information from an SNS contact (regarding a job vacancy and an educational or vocational course) as dependent variable respectively. Control models for each, minus the weak tie access independent variable, are included for reference.

	Control model (DV = Received information from SNS contact regarding an educational or vocational course)	C2 (model 1, DV = Received information from SNS contact regarding an educational or vocational course)	Control model (DV = Received information from SNS contact regarding a job vacancy)	C2 (model 2, DV = Received information from SNS contact regarding a job vacancy
Access to valuable weak ties		-.98		-1.36ᶦ
BIC =	207	209	199	200
Psuedo R2 =	.04	.05	.07	.10
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 8.12: Analysis C2. Logistic regressions. Unemployment factors predicting previous receipt of potentially useful information via an SNS contact; regarding an educational or vocational course (model 1) and job vacancies (model 2). N = 142. All net of following controls; female, age, SNS use, urban density (urban), advantaged inherited background, degree or above educational attainment, high internet skill.

Access to weak ties in career information networks is not found to significantly effect receipt of either form of information via an SNS contact. However, models operationalising information regarding a job vacancy as dependent variable suggest that access to weak ties may be having some impact. First, the negative coefficient estimate is approaching statistical significance (.052). Second, although the BIC value of model 2 does increase from that of the control model, a jump from .07 to .10 in the value of pseudo r-squared suggests inclusion of the weak tie access indicator is helping explain some variance within the dependent variable.

Analysis C3 (Table 8.13) therefore explores this possible relationship further as a basis for analysis of stratification of weak tie effects. Four indicators are interacted with the weak tie access variable, denoting; a degree-level or above education, advantaged inherited social status, being female, and CAMSIS scores of jobs respondents were made redundant from. This produces four models. For efficiency control models as comparison points are not shown.

DV = Received information from SNS contact regarding a job vacancy	Model 1 (Interaction = weak tie access with degree-level education)	Model 2 (Interaction = weak tie access with advantaged inherited social status)	Model 3 (Interaction = weak tie access with female)	Model 4 (Interaction = weak tie access with CAMSIS score)
Weak tie access	-.28	-1.05	-1.35	2.06
Interaction	-15.80	-15.03	-.03	-.10
N =	142	142	142	141
Key: ᶦ p<0.1 * p<0.05 ** p<0.01 *** p<0.001				

Table 8.13: Analysis C3. Logistic regressions. Previous receipt of information regarding a job vacancy from an SNS contact predicted by access to weak ties. Independent variable interacted with; degree-level (or above) educational attainment (model 1), advantaged inherited social status (model 2), female (model 3), male CAMSIS score (model 4). Net of following controls; female, age, SNS use, urban density (urban), advantaged inherited background, degree or above educational attainment, high internet skill. Additional controls; male CAMSIS score (model 4).

Interactions tested produce results which show no significant effect on receipt of information via SNS regarding a job vacancy. Coefficient estimates in models 1 and 2 are unusually large, and likely a result of low case numbers within categories skewing results. No evidence of a stratification of effects of weak tie social capital are found.

Tests within Analytical Theme C find no evidence as to the efficacy of having access to weak tie social capital within career management outcomes. These results are largely inconsistent with the research literature, in that access to valued weak ties should provide additional opportunity through access to original information (Lin, 1999). SNS are seen as facilitators of such valuable weak tie social capital (Rainie and Wellman, 2012), although no relationship is found between access to weak ties and receipt of potentially valuable information via SNS. These results do, however, lack temporal context. Access to valued weak ties at the time of data collection could be being compared to receipt of information from an SNS contact several years prior to that.

Although many studies identify social capital ultimately as a proxy of structural disadvantage – a reflection of low status in society (e.g. Lin and Dumin, 1986; Verhaeghe *et al*, 2015) – no evidence is found presently of significant interactions between social capital access (specifically to weak ties) and social position indicators. It must be noted however that stratification of returns are not tested.

8.4 Conclusion

Findings presented are reflected on in relation to the two broad groupings of research questions that guide research. First, limitations are considered as caveats to these findings.

The main outcome deployed in analyses – gaining re-employment – can be a reductive indicator in some circumstances. Any respondents who made alternative choices in response to being made redundant, that in most circumstances would be considered positive – such as studying a degree – are classified as still unemployed at the time of data collection if paid work was not taken alongside study. Taking early retirement, or not re-entering the workforce through having to care for a family member are other examples not taken into account. Despite these caveats, the outcome operationalised is considered broadly valid due to intentions of seeking work (through engagement with SDS), and a majority of the sample having exited unemployment at the time of data collection.

Another caveat is in relation to indicators denoting receipt of information. Although broadly indicative of whether people have received potentially valuable information through contacts, this information is not pegged directly to a successful outcome, such as securing a job, in the data. Also, a lack of receiving information post-redundancy does not necessarily equal lack of resources. Some respondents may secure another job quickly without the need for information, and therefore may not request it from contacts.

There are also sample biases that should be taken into account. Respondents are actively engaged with a skills agency to better their prospects of re-employment. The sample is perhaps over-representative of people who place importance on career management.

8.4.1 SNS utility in career management

The analytical strategy employed a literature-driven approach to interrogate the role of SNS. First, predictive relationships between SNS use and a bonus to career management (Rainie and Wellman, 2012) were tested directly via regression modelling. The bonus to career management is measured via exiting unemployment following respondents being made redundant from employment, whilst also controlling for job quality. SNS use was not found to directly impact unemployment exit, nor was instrumental use of SNS via receipt of potentially valuable information towards respondent career management. In exploring underlying logic with regards the utility of SNS in career management, very limited support is found. Factors reflective of, or contributive to social network composition that are found to be particularly affected during a spell of unemployment (Morris, 1984; Morris and Irwin, 1992) did not have anticipated effects on career management. A significant effect of feeling isolated following redundancy was found, but the direction (positive) opposed reasonable logic. The suggestion that feeling isolated makes respondents more likely to receive potentially valuable information via SNS is therefore likely a result of a sampling or measurement quirk.

Finally the role of weak ties within career management was explored. Access to weak ties that respondents valued for utility in career management did not predict anticipated boosts (Granovetter, 1973; Lin, 1999) to either likelihood of re-employment or receipt of advantageous information. Together, results suggest that SNS use, social capital use, and access to weak ties do not help in career management.

8.4.2 The second-level digital divide and distribution of social capital effects

The role of the second-level digital divide (Hargittai, 2008a) within career management has been a consistent focus of this Thesis. This is because within hypothesised gains to career management from internet use, and in particular SNS use to manage social capital, differential outcomes are of particular sociological interest. The second-level digital divide however was explored in less detail than in some other analysis chapters on the basis of production of results consistent with those in Chapter 7. No evidence was found of differential outcomes to career management from SNS use in Chapter 7, which was the case in more limited sets of analysis presently. Online skill, found within research literature to be essentially a proxy of structural disadvantage (Hargittai and Hinnant, 2008), is not found to be a factor mediating between career outcomes and productive internet use. Evidence refuting the presence of a systematic divide is also produced through the findings that neither SNS use, or more instrumental use to gain information from contacts make a difference to exiting unemployment.

Although research literature analysing distribution of effects of instrumental social capital use (e.g. Lin *et al*, 1981) find that effects differ according to social position, present results suggest no such systematic patterns occur within the present sample. These results pertain to effects of social capital expenditure, rather than effects, because no significant effects are found.

The next Chapter (Conclusions) evaluates these results in wider context of the Thesis as a whole.

Chapter 9: Conclusion

9.1 Introduction

SNS use within career management is hypothesised to be of great potential benefit towards career attainment (Rainie and Wellman, 2012). This is because such platforms within societies where internet connectivity is ubiquitous allow individuals to develop and maintain weak tie networks. This enhanced social capital exerts a multiplier effect on personal capital (Bourdieu, 1986). However, an analysis across a wide range of social groups, career-related outcomes and data sets has provided little evidence to support that claim.

The conclusion of this Thesis takes the opportunity to condense findings from each linked investigation that are the subject of analysis chapters in order to reflect on aggregate-level findings in context of research questions. These reflections are situated within consideration of research limitations and the wider research literature. Recommendations based upon these reflections for future research and implementation of findings follow.

9.2 Limitations

Almost inevitably with a research project of this scope and ambition, unintended weaknesses have become apparent. Understanding these helps improve additional research and helps to understand present findings. Four main weaknesses of the research are identified.

9.2.1 Indicators employed

The translation of concepts often not originally designed with reference to quantitative research into statistically measurable indicators was a particular challenge of this research, as was positioning relevant indicators within compelling and sensible analytical designs.

Design of the survey question which generated data upon which the online skill level indicator was derived was consistent amongst the three surveys disseminated. It was also based upon an indicator previously used within research on primary data (Hargittai and Hinnant, 2008), which produced findings consistent with the wider research literature (e.g. Hargittai and Hsieh, 2013; van Deursen and van Dijk, 2014). These showed that skill level predicted productive internet use, and that skill was predicted by educational attainment. In present primary analyses, skill level was not found to be a significant factor mediating productive SNS or internet use in any tests. The only substantive difference in how the variable was constructed and employed occurred in variable operationalisation. Hargittai and Hinnant (2008) employ it as a metric variable within regression analysis on a scale of 5-25 (p. 616). Presently, this scale is reduced to categories, primarily in response to low case numbers. Skill level is theoretically important to this Thesis, but on reflection it is difficult to operationalise in a meaningful way. As internet use is becoming more common (Kemp, 2019) people are likely adapting how they use it all the time, in response to the dynamism of the medium. A potential consequence is that internet skill level is perhaps too fluid for a fixed criteria across time-points and social groups. Therefore it is difficult to know before data is collected what distinctions are important to assess within a given study.

Analysis of primary sample data also places significant weight on identification of successful career outcomes (career management success) as a basis upon which to assess the utility of SNS use. A consequence of choosing case studies as sites of analysis clustered around events or circumstances deemed likely to pose additional challenges to career management was that measurement of successful career outcomes were far from straightforward. This was particularly the case with regards to the further education student (Chapter 6) mothers' (Chapter 7) samples. In both cases conventional (e.g. wage levels – Ericksen and Yansey, 1980) outcomes were not seen as appropriate. This led to measurement of subjective optimism (or positivity) surrounding respondent careers. Comparison to more conventional outcomes via identification of significant markers of personal characteristics showed that these subjective indicators did not perform as expected. For example, education did not predict high levels of positivity (7.3), but is an established predictor of wage levels (e.g. Hayward *et al*, 2014; Naylor *et al*, 2015).

9.2.2 Unintentional sample bias

This limitation also pertains to primary data. Some intentional bias (internet user respondents only) was built into the primary data collection in accordance with the focus on internet users within the second-level digital divide (Hargittai, 2008a). Therefore, collecting survey data online seemed a logical approach. On reflection these online surveys likely required a reasonable level of skill to navigate successfully, and literacy to understand fully. It seems likely that relatively skilled users are oversampled in primary data case studies as a result. Other techniques could have been employed to collect data, such as telephone surveys. But these produce different biases. In the example of telephone surveys, selection of numbers to call via a telephone directory would likely oversample older people, as young people increasingly rely on mobile phones rather than landlines (Rainie and Wellman, 2012). Further, more savvy individuals may not be publicly listed in directories to avoid unsolicited calls.

9.2.3 Difficulties of survey research

Other difficulties within, and raised through collection of data via an online survey instrument are briefly discussed in 3.4.5. Implications for both this research and the wider academic research structure warrant further discussion. The primary difficulty with regards consequences for this research was low case number generation. A great deal of effort went into recruitment of gatekeepers through which to disseminate the surveys, which yielded relatively disappointing returns in the form of case numbers. It is likely that low case numbers affected statistical power of analyses, particularly those presented in Chapters 7 and 8. Financial resources were also spent in developing survey instruments (pilot respondent reimbursement) and in incentivising respondents to fill them in (prize draw vouchers).

It was felt that incentives were needed to attract reasonable response numbers, in order to make them stand out amongst the crowd of organisations seeking consumer insights within ‘knowing capitalism’ (Savage and Burrows, 2007). It seems extremely likely that these incentives were responsible for attracting unwanted attention in the form of fraudulent responses (described in 3.4.3.3) to the mothers’ survey. It was perhaps fortunate that the algorithm (or the person(s) responsible) used to exploit the survey was not sophisticated, and the deception was easily spotted. Non-detection of fraudulent responses is potentially a great concern within online survey research.

It would perhaps be best to keep online survey research limited to particularly motivated populations, rather than people who have relatively little stake, as present research did. Use of incentives to attract respondents, based on present experience, is unlikely to be worth the cost if the research has a small budget. If incentives are used, it is recommended that exposure of a survey recruitment advert is limited to relatively closed spheres. Social media proliferation likely drew unwanted attention in the case of this research. The academic literature was searched regarding the best level of reimbursement to offer respondents, but it was found that this is an under-researched area. Development of a methodological literature on this subject is important and is required for future research.

9.2.4 Separation of effects – internet and SNS use

Separation of effects stemming from internet and SNS use is largely not achieved by this research, in two ways. First, causal relationships (e.g. certain uses of SNS cause increase in likelihood of job attainment) are very difficult to establish, and associations are instead relied upon as ‘suggestive’ evidence. This is the case here, and within the wider research literature. If an analysis finds that informational use of SNS (e.g. a respondent has previously received information regarding a job vacancy from an SNS contact) significantly predicts job attainment, causality is not addressed. It could be that those successful in career management are also more successful SNS users. A further limitation that arises within the example given is a lack of contextual connection amongst factors measured. The piece of information received is not necessarily related to attainment of that particular job.

The second way in which effects from internet and SNS use are not well separated in this research lies in identifying significantly different effects stemming from use of either. This is challenging due to a lack of difference in respective internet-using and SNS-using populations. Most internet users in the UK use SNS (Kemp, 2019), so separation of distinctly different effects of usage of either is difficult due to the large overlap in populations.

9.2.5 Contextual findings

A strength of the sampling strategy is that research questions are explored in context of respondent populations to which career management is particularly important. Primary case studies, such as students about to leave further education, or people who have recently lost their job through being made redundant are particularly compelling contexts for policy makers and academia alike. It was also expedient to conduct analyses which included looking at effects of SNS use on job acquisition amongst respondent populations who are more likely to be seeking work. This also applies to sub-samples selected for analysis amongst secondary data, such as the population of jobseekers utilised within Understanding Society.

Conducting analyses amongst relatively disparate groups likely increased the probability of generating findings that do not complement each other, or are sometimes contradictory. What works for a 21 year-old student may not work for a 55 year-old former oil and gas worker. The ‘second-level digital divide’ (Hargittai, 2008) theory denotes this.

Findings from identical, or similar, patterns of data interrogation did not produce uniform results. A limitation of requiring context to understand different findings is that they are more difficult to communicate to stakeholders, and thus render impact generation more difficult. Although the null hypothesis is broadly accepted in relation to Rainie and Wellman’s (2012) work, there are caveats within findings that must be acknowledged.

9.3 Findings

Having considered limitations of this research, aggregate findings are discussed in relation to research questions and the wider research literature.

9.3.1 Research Question A: Is SNS use beneficial to career management?

Within this overarching first research aim, utility of social capital expenditure (with a focus on weak ties) is explored (Granovetter, 1973; Lin, 1999) because it is a key theoretical plank behind the reasoning of SNS utility in career management (Rainie and Wellman, 2012). The role of internet use in relation to potentially beneficial effects for career management also falls under this category, because SNS are a part of the internet sphere.

Evidence relating to Research Question A was generated from analyses of all data sets. Although some variation in findings exists, an overall conclusion that this Thesis finds no substantial support for utility of SNS use in career management can be reasonably drawn. Analysis of three of the five data sets (Understanding Society, Mothers, Redundancy) finds no evidence that indicates SNS use (absolute or informational/productive) is associated with preferential career management outcomes. Of the other two data sets analysed, support for SNS utility found through analysis of the further education student data set is tentative. The reasoning behind this is that although receipt of information from an SNS contact regarding a job vacancy is not found to predict a boost to career management, receipt of information regarding courses is. It is reasoned that this information is likely more pertinent to the aggregate career stage of the sample. Therefore, support is conditional, a matter of interpretation. Support found through analysis of OxIS data is not conditional however. SNS use is positively associated with attainment of jobs advertised online, which are in turn found to be of a higher quality.

With regards social capital use more generally, some support is found for utility within job attainment, but not quality. Of data where social capital use within career management is analysed (Understanding Society, Further Education, Mothers, Redundancy) levels of support are mixed, and relatively nuanced. Understanding Society analysis finds that social capital use within a job search is positively associated with exiting unemployment, but not quality of those jobs. Further Education data analysis finds no support for utility of contact use in career management. Analysis of Mothers' data finds some evidence of a career management boost for those with access to valued weak ties in context of career advice, suggesting that social capital use overall does have an effect. Analysis amongst the Redundancy sample finds no evidence relating to composition of social network on career management outcomes. Although similar analysis of Understanding Society data finds that high levels of employment amongst social contacts is positively associated with unemployment exit, in line with similar analysis by others (Cappellari and Tatsiramos, 2011; 2015). These findings diverge somewhat from those of social capital literature, where more unequivocal support is found for use of information from contacts in predicting positive employment outcomes (e.g. Granovetter, 1973; Lin, 1999; Fuels *et al*, 2014). Many analyses that identify social capital effects within this context find that benefits, or levels of benefit, are contingent upon social position (e.g. Lin and Dumin, 1982; Morebeek *et* al, 1995; Verhaeghe *et al*, 2015). It is perhaps the case that present research did not separate out such nuance effectively enough, and unidentified variation in outcomes affected clarity of aggregate-level findings.

Within social capital effects, although analysis of Mothers' data found some support for efficacy of access to weak ties within career management, other primary data analyses did not replicate these findings. No support for a bonus to career-related outcomes is identified in analyses or Further Education and Redundancy data. Secondary data did not provide means to differentiate personal ties between strong or weak. Therefore, in summary, it must be concluded that support for 'the strength of weak ties hypothesis' (Granovetter, 1973; 1974) is not replicated here.

Finally, with regards to efficacy of wider internet use as part of career management strategy, evidence is still mixed, but provides tentative support. Analysis of OxIS data found that attainment of jobs found online is in turn linked to job quality, and that activity that supports human capital development (Wei and Hindman, 2011; van Deursen and van Dijk, 2014) is also linked to these positive career management outcomes. However, analysis of Understanding Society data refutes this. Job-searching online did not affect most employment outcomes in regression analyses. Results pertaining to Redundancy data find no bonus to career management outcomes through productive internet use, although results related to the other two primary data sets identified that productive internet and SNS uses are significantly related. The latter trend was also identified in analysis of OxIS data. These results suggested that the same SNS users gaining theoretical benefits (e.g. information from contacts regarding career management) were those also using the internet to enhance human capital. This suggestion has two implications. First, that productive internet use (inclusive of productive SNS use) is not necessarily that productive, because it is not consistently linked to positive career management outcomes presently. Second, that differential use of the internet does appear to follow a pattern, which has implications related to the second-level digital divide (Hargittai, 2008a).

9.3.2 Research Question B: Who embraces the career-enhancing capacity of SNS?

This Thesis finds only limited evidence for utility of SNS within career management – through direct analysis and exploration of key theoretical planks – to the extent that it must be concluded that no support for Rainie and Wellman's (2012) conceptualisation of SNS as particularly beneficial in career management is found. This however, does not mean that SNS are not useful tools within career management. Not observing statistically significant associations is not proof that effects (i.e. career management benefits of SNS use) do not exist. It merely means that they have not been observed, in concrete terms. Irrespective of whether there is a benefit, understanding who is embracing SNS to expand their careers is useful. It may help identify social groups who are using strategies with no evidence of beneficial impact who might, therefore, be targeted to adopt strategies that utilise a stronger evidence base pertaining to effectiveness. Therefore, identification of population-level patterns of theoretically beneficial use – the second strand of this investigation – is not devalued by findings related to the first strand.

The second-level digital divide theory (Hargittai, 2008b) posits that however valid Rainie and Wellman's (2012) assertions about SNS utility may be, systematic forces exclude those who could benefit most from career-management boosts. Skills required to use the internet productively are unevenly distributed amongst internet users (Hargittai and Hinnant, 2008). This distribution ultimately represents entrenched structural inequalities (Hargittai, 2008a). One of the most obvious ways this is evidenced in research literature is identified through educational attainment. This is positively associated with productive internet use (Wei and Hindman, 2011; van Duersen and van Dijk, 2014), and skill level is the factor that mediates educational attainment and productive internet use (Hargittai, 2008c; Hargittai and Hinnant, 2008). Educational attainment performs similarly in relation to career management generally, predicting wage levels better than any other factor, for example (Hayward *et al*, 2014; Naylor *et al*, 2015). A cohort effect predicting productive internet use is also emphasised through the theory of digital natives (Prensky, 2001).

Present findings do suggest that systematic population-level patterns are operating in relation to productive internet and SNS use. However, little else is found to develop flesh out such a conclusion beyond this relatively basic level. The positioning of this conclusion is shaped by findings pertaining to the role of online skill. Analyses consistently found no significant role of skill within productive internet use. Skill neither predicted such use – as it should theoretically and has in other investigations – nor was it predicted by personal characteristics highlighted within the literature as being important, such as education. However analyses conducted within Chapter 4 that bypass online skill variables do find that educational attainment consistently predicts productive internet use, as does age negatively. A lack of evidence in this investigation when online skill is operationalised as the key linking component means that it must be concluded that beyond systematic patterns of differential use, no support is found for the implications of the second-level digital divide within SNS use as a tool for career management.

9.3.3 Rethinking the network society perspective

It is suggested in Chapter 1 that, based upon a review of relevant research literature, Rainie and Wellman's (2012) characterisation of SNS as a transformative and egalitarian tool for career attainment is likely not rooted in good science. The work that they present does not account for the second-level digital divide in any meaningful way, and therefore does not constitute a rigorous investigation of the theoretical aspects that lead to the composition of their compelling central assertion. Despite this, their work is influential amongst leading academics (MIT Press, 2019). As someone working in academia, the Researcher also regularly sees career management advice for academics informed by the same school of thought (SNS use equals expansion of social capital, that equals better career outcomes). Literature on networking has a tendency to be overwhelmingly positive about the benefits (e.g. Rainie and Wellman, 2012; Veletsianos, 2012; Kindley, 2015; Knight and Kaye, 2016). As evidence from this Thesis and elsewhere suggests, such a calculation is not clear cut. More attention should be paid to work that goes into generating attractive headlines, rather than taking an attractive headline derived from incomplete work at face value.

9.3.4 Networking and career management skills

As a key component of career management skills (SDS, 2012), findings suggest that conceptualisation of networking requires further attention. If networking is found to produce career-related benefits in some research, it is quite logical that some will generalise the equation as networking equals better careers. What this research suggests is that benefits are clear. Whilst it is highly likely that forms of networking can be beneficial, not all is. As an example, producing links characterised by mutual goodwill and respect with professors may yield positive benefits for an early-career researcher (ECR). Similar links fostered with regular drinkers at the ECR's local pub are less likely to bring tangible benefits. Within study and application of CMS, it would be beneficial to conceptualise networking in this more nuanced way.

9.3.5 Implications for networked society

The literature guiding formulation of present research questions, and findings from interrogation of data provide an empirical counterbalance to the enthusiasm with which Rainie and Wellman (2012) and others frame benefits of SNS use in a career management context. This enthusiasm is perhaps understandable in relation to certain – likely privileged - social groups, but this thesis shows that there is room for nuance. Things are rarely 'all good' or 'all bad'.

Contextual findings showing variation in SNS utility amongst case study groups highlights the requirement for more science within this area. Rainie and Wellman (2012) very usefully draw attention to the potential benefits to upward mobility through career attainment that SNS use can theoretically bring. This thesis finds that in reality, multiple barriers negate this theoretical usefulness. Beyond these findings, there is great opportunity to further identify social groups that generate less utility from SNS use, identify the barriers inhibiting utility, and find ways to eliminate or mitigate such barriers.

9.3.6 Latent ties

Latent ties – potential but not yet activated (Haythornthwaite, 2002) – are not operationalised through specific indicators within this study, and are therefore not directly studied. However they are important in the conceptualisation of beneficial SNS use within a career management context. This is because SNS provide a structure that articulates extended properties of networks (Boyd and Ellison, 2007), such as showing who is a connected to the user's connections. Present findings pertaining to social capital generation and use via SNS suggest logically that SNS are not particularly beneficial for activating and gaining information from potentially beneficial latent ties, because benefits from SNS use are not found.

9.4 Future work

This final section takes the opportunity to comment on what would be productive avenues for future research in relevant areas, based upon the experience of conducting this study.

9.4.1 Social capital activation

Focus relating to the utility of useful connections towards career attainment – relationships generated or maintained in offline and online contexts – can place too much importance on the issue of social capital accumulation, in arenas where social or upward mobility is the priority. Because of structural imbalances in how social capital is distributed, interventions are currently being played out across the world that seek to 'give' people from non-traditional backgrounds access to valuable social resources. Examples include the Taylor Bennett Foundation (taylorbennettfoundation.org), which builds up the professional networks of black and minority ethnic graduates within the public relations industry, facilitating their entry into a sector which values knowing the right people, and under-represents non-white employees (McGregor *et al*, 2019).

Compelling evidence from psychological studies suggests that patterns of activation of social capital may be stratified in ways similar to which we see affecting access to social capital. Women (Operti & Lampronti, 2018), and individuals of low status occupations (Smith *et al.*, 2012) for example, are found to perform relatively poorly at social network structure recall or activation of personal networks under conditions of stress and competition. Such conditions are comparable to navigation of employment markets or corporate culture.

Therefore, greater attention on activation of social capital is likely important within policy formation aimed at increasing potential for upward mobility via accumulation of social capital. Evidence suggests that sole focus on social capital accumulation could detract from well-intentioned policy work. To justify consideration of social capital activation at policy level, the need for rigorous social scientific enquiry is urgent.

9.4.2 Non-generic SNS research

This research did not differentiate between individual SNS platforms in investigating SNS utility in career management. Specific attention placed upon career-focused platforms such as LinkedIn would add depth to such an investigation. Different platforms, as in many free markets, tend to fulfil different niches. Aggregation of these platforms in research may underplay nuances associated with particular types of SNS, especially those with career management focus. The data gathered was dominated by the major SNS sites such as Facebook and Twitter, and therefore findings are representative of all SNS use, rather than evaluating impact of use of any particular site. There is scope for exploring whether the trends produced by this research hold true for specialist sites.

9.4.2 Linking information to outcomes in SNS career management research

A development of this research would be greater separation of cause-and-effect in relationships explored between potentially useful information received via SNS and related career outcomes. This research investigated the relationship in large part through recording whether respondents had received specific forms of information from SNS contacts previously and tested this for association with job attainment or self-assessment of career position or trajectory. The two components of such tests are not necessarily related to each other. For example, a respondent may have exited unemployment recently, and received information about a job vacancy from an SNS contact before. Such a relationship is only suggestive that social capital management via SNS and positive employment outcomes are linked. A better investigation of cause-of-effect would investigate outcomes specific to receipt of potentially beneficial information.

9.5 Summary

In summary, the work presented in this Thesis provides a comprehensive investigation into the utility of SNS use within career management. Results suggest that potential gains from use are over-hyped, and serve to encourage further research investigating Rainie and Wellman's (2012) conceptualisation. It seems likely that benefits are there to be gained, as are those from social capital use more generally. But those gains would be conditional and specific to various contexts. This conclusions section calls for nuance to be taken into account when considering the benefits of career-oriented networking, amid the clamour to discover magic bullets for success and the creation of equality of opportunity. In the Introduction to this Thesis (Chapter 1), it is stated that a review of literature pertaining to the concepts that form the key theoretical planks of Rainie and Wellman's work suggests that many have interpreted the topic of this Thesis as 'case closed', despite research findings that at the very least provide mitigating circumstances within SNS utility. Results were not quite as hypothesised. It was expected that SNS use would be found to be beneficial on the condition of skill, which in turn was a proxy of structural inequality. SNS were not found to be this effective in career management, and skill was not identified as a confounding factor (although results suggest second-level digital divide elements do indeed matter). These unexpected findings serve to underscore the point originally made in the Introduction. Good science does take a long time to produce, and unpacking effects and what they mean for different social groups entails very complex work. But just because it is difficult, and often immediate headlines are not generated does not mean we should abandon balanced, objective enquiry in favour of red herrings and the next shiny research topic.

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Appendices

Please note. All surveys inserted as appendices are converted PDF documents (only possible export format from survey provider). The formats as seen in this Thesis document are the best that I could do for a printed version. However, to download the PDF's please visit the following link, which contains appendices 1a, 1b and 1c: https://github.com/kaneneedham/PhD-Utility-of-SNS-within-career-management

Appendix 1a: Further education student survey

FE Students - Internet and career survey

Introduction and student status

Thank you for agreeing to take part in our survey.

We are interested in how people who are due to graduate or have recently graduated from a course in Further Education use both the internet and their social contacts to help their careers.

The following survey will ask you basic questions about your background, and your experiences of using the internet and other sources to find out information which may benefit your career.

Your responses to the questions asked in this survey will be strictly confidential and will be stored electronically in line with University of Stirling data protection guidelines. Some aggregated data may be shared with your College, but your responses will not be personally identifiable (eg - your College may be told that 76% of its students who took part used Facebook, but individuals will not be identified).

Your are free to withdraw from answering the questions at any point.

If you enter your email address when asked at the end of the survey you will be entered into a prize draw to win 1 of 8 £20 Amazon vouchers.

Winners will be contacted towards the end of Summer.

This survey contributes to a study co-funded by Skills Development Scotland and the Economic and Social Research Council. For further information please contact the project lead researcher:

Kane Needham, 4S24 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 07791558737. EMAIL: kane.needham@stir.ac.uk

Kane is carrying out the survey under supervision of Dr Dave Griffiths. If you wish to make any further enquiries or a complaint Dave's address is:

3S6 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 01786 467729. EMAIL: david.griffiths@stir.ac.uk

Please select the option that best describes your status as a student:

- Due to finish course within 6 Months
- Due to finish course within 3 Months
- Finished course in the last 3 Months
- Finished course 3-6 Months ago
- None of the above

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Your career - still on course

This is a short section of questions designed to find out what you plan to do next after you finish your course, and how you feel about the direction of your career.

Which College do you study at?

- Argyll College
- Ayrshire College
- Borders College
- City of Glasgow College
- Dumfries and Galloway College
- Dundee and Angus College
- Edinburgh College
- Fife College
- Forth Valley College

- Glasgow Clyde College
- Glasgow Kelvin College
- Inverness College
- Leith School of Art
- Lews Castle College
- Moray College
- New College Lanarkshire
- Newbattle Abbey College
- North East Scotland College
- North Highland College
- Orkney College
- Perth College

- Sabhal Mòr Ostaig
- Scotland's Rural College
- Shetland College
- South Lanarkshire College
- West College Scotland
- West Highland College
- West Lothian College

Which best describes what you intend to do once you finish your course?

- You plan to study another course
- You plan to get a job
- You are unsure at the moment

How positive do you feel about where you will be in terms of your career in one year's time? **Please rank on a scale of 1-5:** *Required*

- 1 - Very positive

- 2 - Positive

- 3 - Neither positive nor negative

2/18

○ 4 - Negative

○ 5 - Very negative

Your career - finished course

Which College did you study at?

- Argyll College
- Ayrshire College
- Borders College
- City of Glasgow College
- Dumfries and Galloway College
- Dundee and Angus College
- Edinburgh College
- Fife College
- Forth Valley College
- Glasgow Clyde College
- Glasgow Kelvin College

- Inverness College
- Leith School of Art
- Lews Castle College
- Moray College
- New College Lanarkshire
- Newbattle Abbey College
- North East Scotland College
- North Highland College
- Orkney College
- Perth College
- Sabhal Mòr Ostaig
- Scotland's Rural College

Shetland College

South Lanarkshire College

West College Scotland

West Highland College

West Lothian College

Are you currently employed?

Yes - employed full-time (35 hours or more per week)

Yes - employed part-time (less than 35 hours per week)

No

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Your career - finished course (full-time employed)

This is a short section of questions designed to find out what stage your career is at now that you have finished your course, and how you feel about the direction of your career at this stage.

Which of the following best describes your (main) job?

- Its a great job for you to have at the moment
- It is a stepping stone towards your desired career path
- It is temporary whilst you consider your options for the future
- It is temporary, and you are actively looking for a new job
- It is a job to earn some money before you start a new course

How positive do you feel about the direction of your career at the moment? **Please rank on a scale of 1-5:** *Required*

- 1 - Very positive
- 2 - Positive
- 3 - Neither positive nor negative
- 4 - Negative
- 5 - Very negative

Your career - finished course (part-time/unemployed/other)

This is a short section of questions designed to find out what stage your career is at now that you have finished your course, and how you feel about the direction of your career at this stage.

Which of these best describes your employment status since finishing your course?

- You are not sure what to do next
- You have started another course
- You are working part-time in a job which you are happy with
- You are working in a part-time job which you are unhappy with
- You are currently unemployed, but are looking for a full or part-time job
- You are currently unemployed, but plan to start another course in the near future
- None of the above

How positive do you feel about where you will be in terms of your career in one year's time? **Please rank on a scale of 1-5:**

- 1 - Very positive
- 2 - Positive
- 3 - Neither positive nor negative
- 4 - Negative
- 5 - Very negative

Your details

Which of the following best describes your gender?

- Male
- Female

What age are you?

Which of these best describes your ethnicity?

- White UK (Scottish, British, English, Northern Irish, Welsh)
- White other

Asian

Black

Mixed race

What language do you speak when you are at home?

English

Other

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Your details

Which of these best describes the area in which you live?

- Urban - city/large town
- Rural - small town/village

What is the highest level of qualification that you have achieved, or are currently studying for?

- SCQF Level 1 - National 1
- SCQF Level 2 - National 2, National Progression Award (level 2), National Certificate (level 2)
- SCQF Level 3 - National 3/Skills for Work National 3, National Progression Award (level 3), National Certificate (level 3)
- SCQF Level 4 - National 4/Skills for Work National 4, National Progression Award (level 4), National Certificate (level 4), SVQ1, Intermediate 1
- SCQF Level 5 - National 5/Skills for Work National 5, National Progression Award (level 5), National Certificate (level 5), SVQ2, Intermediate 2

- SCQF Level 6 - Higher, Skills for Work Higher, National Progression Award (level 6), SVQ3, National Certificate (level 6), Professional Development Award (level 6)
- SCQF Level 7 - Higher National Certificate (HNC), Advanced Higher, Scottish Baccalaureates, SVQ3, Professional Development Award (level 7)
- SCQF Level 8 - Higher National Diploma (HND), SVQ4, Professional Development Award (level 8)
- SCQF Level 9 - Ordinary Degree, SVQ4, Professional Development Award (level 9)
- SCQF Level 10 - Honours Degree, Graduate Diploma, Graduate Certificate, Professional Development Award (level 10)
- SCQF Level 11 - Masters Degree, Postgraduate Diploma, Postgraduate Certificate, SVQ5, Professional Development Award (level 11)
- SCQF Level 12 - Doctoral Degree, Professional Development Award (level 12)

Do you intend to study a degree-level course in the future?

- Yes
- No
- Unsure

Have already studied/started studying

Do you live with your Parent(s) for most of the year?

Yes

No

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Your details

What is your current housing tenure (or Parents tenure if you live with them)?

- Own your own home (with mortgage or outright)
- Private rented
- Rented - social/council housing
- Other rented (eg University campus)

Which of these best describes your **Mother's** highest level of education?

- University
- Post-16 education (ie after manditory education, but did not go to University)
- School leaver
- Don't know/unsure/not applicable

Which of these best describes your **Father's** highest level of education?

- University
- Post-16 education (ie after manditory education, but did not go to University)
- School leaver
- Don't know/unsure/not applicable

Did you receive EMA (Education Maintenance Allowance) whilst studying on your current or most recent course?

- Yes
- No

Job searching and career advice

If you have used any of these sources to look up information regarding educational or career training, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very useful	2 - Useful	3 - Somewhat useful	4 - Not useful	5 - Not useful at all	6 - Never used
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
Career websites (eg Prospects.ac.uk or	☐	☐	☐	☐	☐	☐

myworldofwork.co.uk)

Career advisor (in person)

Training company websites (eg skillstraininguk.com)

Educational provider websites (Universities/Colleges)

Asked someone you know through a social networking

site

Newsletters you have subscribed to online

Newspapers or magazines

Asked someone you know (not through a social

networking site)

If you have used any of these resources to help you find a job, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very useful	2 - Useful	3 - Somewhat useful	4 - Not useful	5 - Not useful at all	6 - Never used
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐

Newspaper adverts

Jobcentre or other career advisors

Asked someone you know through a social networking

site

Job listing websites (eg reed.co.uk or 'Universal

Jobmatch' at gov.uk/jobsearch)

Contacting potential employers

Career advice websites (eg myworldofwork.co.uk)

Asked someone you know (not through a social networking site)

Think about 3 people that you would be most likely to ask for advice from regarding your own career. **For each person, please select the option that best describes your relationship with them:**

	Relationship with person										
	Partner	Close family member	Other family member	Close friend	Someone from your course	Work colleague	Distant friend/acquaintance	Friend of a friend	Tutor/member of staff at College	Friend of a family member	Other
Person 1											
Person											

2

Person

3

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Online activity

Where do you use the internet, and how often?

Please don't select more than 1 answer(s) per row.

	More than once a day	Once every day or two	Once a week	Once a Month	Longer than one Month ago, or do not use
At home					
At College					
At work					
On the move (mobile data connection)					
At friends'/partner's home					
Public WiFi - places such as bars, libraries, coffee shops					

What kind of devices do you use to access the internet regularly (at least once per week)? **Please select all that apply:**

- Your own PC or laptop
- A PC or laptop at College
- A PC or laptop at work
- Someone else's PC or laptop
- Your own smartphone/tablet
- Someone else's smartphone/tablet

Please rate how well you would say you understand the following technical terms on a scale of 1-5? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 - Completely understand	2 - Mostly understand	3 - Somewhat understand	4 - Do not really understand	5 - Do not understand at all
Cookies					
Search engine					
Phishing					
URL					

Upload					

How regularly do you perform the following activities on the internet? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	Regularly (daily/weekly)	Semi-regularly (Monthly)	Sometimes (1-2 times per Year)	Never
Look up job vacancies				
Find career advice				
Watch movies/TV programmes or sport				
Research educational or vocational course information				
Research financial information				

Shopping	☐	☐	☐	☐
	☐	☐	☐	☐
	☐	☐	☐	☐
Research health-related information	☐	☐	☐	☐
	☐	☐	☐	☐

Read news

Play games

Research information to help you with

assignments/exams

Your social networking site membership

A social networking site is an internet website which allows you to make a personal profile and add content such as pictures or videos. It allows you to connect with other users and view the content that they have uploaded, as well as to view their list of connections (or 'friends').

Examples of such sites are Facebook, Twitter, Instagram and LinkedIn.

These examples do not include apps such as WhatsApp or Yik Yak, where users don't have a profile.

Do you have a profile on, or are you a member of **any** social networking site?

- Yes
- No

Your social networking site usage

Which social networking sites do you use, and how often?

Please don't select more than 1 answer(s) per row.

	Always using it	Use once every day or two	Use once a week	Use once a Month	Have an account, but do not use it	Have never used
Facebook	☐	☐	☐	☐	☐	☐
Twitter	☐	☐	☐	☐	☐	☐
LinkedIn	☐	☐	☐	☐	☐	☐
Google+	☐	☐	☐	☐	☐	☐
Pinterest	☐	☐	☐	☐	☐	☐
Instagram	☐	☐	☐	☐	☐	☐
Tumblr	☐	☐	☐	☐	☐	☐
Other	☐	☐	☐	☐	☐	☐

Which type of person do you think the following social networking sites are best for keeping in touch with? **Please select all that apply:**

	Don't use this site/not applicable	Partner	Close family member	Other family member	Close friend	Someone from your course	Work colleague	Distant friend/acquaintance	Friend of a friend	Tutor/member of staff at College	Friend of a family member	Other
Facebook												
Twitter												
LinkedIn												
Google+												
Pinterest												
Instagram												
Tumblr												
Other												

Your social networking site usage

Imagine that you **did not use** any social networking sites. For **each type** of person please rate on a scale of 1-5 whether it would be easier or more difficult to maintain the levels of contact that you currently have. **Please place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 = Very easy to maintain current levels of contact	2 = Quite easy to maintain current levels of contact	3 = It would not make a difference	4 = Quite hard to maintain current levels of contact	5 = Very hard to maintain current levels of contact
Partner					
Close family member					
Other family member					
Close friend					
Someone from your course					
Work colleague					
Distant friend/acquaintance					
Friend of a friend					
Tutor/member of staff at College					
Friend of a family member					
Other					

Certain types of social relationships are more useful for getting different types of information from. What types of people (if any) have you received information from through a social networking site for the below list of topics?

	Never requested help/information via a social networking site	Partner	Close family member	Other family member	Close friend	Someone from your course	Work colleague	Distant friend/acquaintance	Friend of a friend	Tutor/member of staff at College	Friend of a family member
A job vacancy											
An educational or vocational course											
Your current/last job											
Membership of an organisation											
Finance											
Your health											
The internet											

	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
or computers											

Have you ever used a social networking site profile to try and further your career (for example to promote yourself to potential employers)?

○ Yes

○ No

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○ Considering doing so in the future

If relevant, please briefly explain what you did through your social networking site profile(s), or intend to do in the future:

Prize draw entry

If you would like to be entered into our prize draw please enter your email address in the box below so that we can contact you if you have won 1 of 8 £20 Amazon vouchers.

Email address:

Finished

Thank you for taking part in our survey. Your answers have been recorded.

Appendix 1b: Mothers survey

Parents of primary school children - internet and career survey

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Introduction and parental status

Thank you for agreeing to take part in our survey.

We are interested in how parents navigate the world of employment and how they use the internet.

The following survey will ask you basic questions about your background, and your experiences of using the internet and other sources to find out information which may benefit your career.

Your responses to the questions asked in this survey will be anonymous and the data will be stored electronically in strict confidence. Only anonymous and aggregated data will be reported in subsequent publications.

Your participation in the survey is entirely voluntary and you are free to withdraw from answering the questions at any point. You are not able to save your answers and return to the same point later on (e.g. half way through the survey).

If you are not happy to give a response to a particular question, you may leave it blank and move on to the next. A couple of questions require responses purely to skip you past questions that are not relevant to you. Once your responses have been submitted, these cannot be withdrawn.

If you enter your email address when asked at the end of the survey you will be entered into a prize draw to win 1 of 10 £20 Amazon vouchers.

Winners will be contacted once the survey has closed in Spring 2017. Your email address is not linked to any of your other survey answers.

This survey contributes to a study co-funded by Skills Development Scotland and the Economic and Social Research Council. For further information please contact the project lead researcher:

Kane Needham, 4S24 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 07791558737. EMAIL: kane.needham@stir.ac.uk

Kane is carrying out the survey under supervision of Dr Dave Griffiths. If you wish to make any further enquiries or a complaint Dave's address is:

3S6 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 01786 467729. EMAIL: david.griffiths@stir.ac.uk

Please indicate that you have read and understood the above text, and are happy to continue on to the survey by selecting 'yes'. If you are not happy to continue on to the survey for any reason, please select 'no'. *Required*

1/24

Parental status

Are you a parent or guardian of a primary school-age child? *Required*

2/24

Your details

Which of these best describes your gender?

- Male
- Female

What age are you?

Which of these best describes your ethnicity?

- White UK
- White other

- Mixed ethnic groups
- Asian, Asian Scottish or Asian British
- African
- Caribbean or Black
- Other ethnic group
- Prefer not to say

Could you describe what language you usually use?

- English is my first language and is the one I use all the time
- My first language is not English but I speak English all or nearly all the time
- My first language is not English and I speak a different language regularly (e.g. with family at home)
- Other/prefer not to say

Your details

Which of these best describes the area in which you live?

- I live within a city or large town (e.g. population of at least 10,000)
- I live in a small town, village or other area - but I am close to a city or large town (e.g. within 5 miles)
- I live in a small town, village or other area - and am more than 5 miles away from a city or large town

What is the highest level of qualification that you have achieved, or are currently studying for?

- University
- Other post-secondary education (i.e. after mandatory education, but did not go to University)
- Secondary education (i.e. high school)

Which best describes where you live at the moment?

3

- I live in a property that I own outright
- I live in a property that I own with a mortgage
- I rent from a private landlord
- I rent from a local authority/social housing
- Other

How many other people live with you at the moment?

- I live alone
- 1
- 2
- 3
- 4

○ 5 or more other people live with me

Your details

Which UK region do you currently live in?

- Scotland
- Wales
- Northern Ireland
- East of England
- East Midlands
- London
- North East
- North West
- South East
- South West
- West Midlands

Yorkshire and the Humber

Which of these best describes your **Mother's** highest level of education?

University

Other post-secondary education (i.e. after mandatory education, but did not go to University)

Secondary education (ie high school)

Don't know/unsure

Not applicable/did not have relationship with Mother

Which of these best describes your **Father's** highest level of education?

University

○ Other post-secondary education (i.e. after mandatory education, but did not go to University)

○ Secondary education (ie high school)

○ Don't know/unsure

○ Not applicable/did not have relationship with Father

5/24

Your family

This is a short section of questions designed to find out how your immediate family is structured. This is of interest to our research as differences between for example, single parents and parents that live together are important.

How many children are you the parent or guardian of?

How many children that you are parent or guardian of from the following age groups live with you at the moment?

	Number of children:			
	0	1	2	3 or more
Pre-primary school age				
Primary school age				
Secondary school age				
Older than secondary school age				

Do you currently live with a partner? *Required*

- Yes
- No

6/24

Your partner

Is your partner in work at the moment (employed or self-employed)?

- No
- Yes, full-time (35+ hours per week)
- Yes, part-time (17-34 hours per week)
- Yes, part-time (16 hours or less per week)

And, if your partner is in work, what is their job title? **Please try and be as specific as possible -** eg if your partner is an 'administrator', state which industry and department they work in:

Current employment 1

Are you current employed **(full-time, part-time or self-employed)**? *Required*

- Yes
- No

Current employment 2

Please answer the following questions regarding your current job in as much detail as possible:

What does the company/organisation that you work for mainly make or do? **If you are self-employed please describe what you make or do:**

More info

What is the title of your main job?

More info

What do you mainly do in this job? Please give a brief list of **up to 3** of your main duties:

More info

Which of these does the income from your main job **before tax** fall into: *Required*

- £1 - £4,999
- £5,000 - £10,999
- £11,000 - £15,999
- £16,000 - £21,999
- £22,000 - £29,999

- £30,000 - £39,999
- £40,000 - £49,999
- £50,000+

Last job (not currently working)

Have you worked in paid employment at all during the period since you became a parent?

Yes

No

Please answer the following questions regarding your last job **in as much detail as possible:**

What did the company/organisation that you worked for mainly make or do? **If you were self-employed please describe what you made or did:**

More info

What was the title of this job?

More info

What did you mainly do in this job? **Please give a brief list of your main duties:**

More info

Which of these did the income from the job **before tax** fall into:

- £1 - £4,999

- £5,000 - £10,999
- £11,000 - £15,999
- £16,000 - £21,999
- £22,000 - £29,999
- £30,000 - £39,999
- £40,000 - £49,999
- £50,000+

Roughly when did you leave this job? **Please give the Month and Year if you can remember:**

And on average how many hours per week did you work in this job?

- 1-16 hours (part-time)
- 17-34 hours (part-time)
- 35+ hours (full-time)

11/24

Current employment status

Which of these best describes your current employment situation? **Please select all that apply:**

- ◌ Employed full-time (35 hours+ per week)
- ◌ Employed part-time (17-34 hours per week)
- ◌ Employed part-time (16 hours or less per week)
- ◌ Not employed and looking for work
- ◌ Not employed and not looking for work at the moment
- ◌ Full-time student
- ◌ On maternity/paternity leave
- ◌ Retired
- ◌ Long-term sick or disabled
- ◌ Family carer
- ◌ Other

Additional career questions

After your primary school-aged child was born, did you take a career break from your job that was **longer** than the statutory maternity/paternity leave period? **If you have more than 1 primary school-aged child, please refer to your youngest:**

- Yes - I took a career break longer than the statutory period
- No - I took the statutory leave/less than statutory leave
- I was not in employment at that time

On a scale of 1-5, how optimistic would you say you are with the way your career is going?

- 1 - Very optimistic
- 2 - Optimistic
- 3 - Reasonably optimistic
- 4 - Not very optimistic

○ 5 - Not at all optimistic

Your networks and childcare

How likely are you to meet new friends these days through the following? **Please rank each 1-5 (1=very likely, 5=not likely at all):**

Please don't select more than 1 answer(s) per row.

	1 = Very likely	2 = Likely	3 = Sometimes	4 = Not likely	5 = Not likely at all
Through work	☐	☐	☐	☐	☐
Through volunteering	☐	☐	☐	☐	☐
Through community organisations	☐	☐	☐	☐	☐
Through parenting groups	☐	☐	☐	☐	☐
Through meeting parents of your child(s) friends	☐	☐	☐	☐	☐
At the school gates	☐	☐	☐	☐	☐
Through hobbies	☐	☐	☐	☐	☐
Through nights out	☐	☐	☐	☐	☐
Through your family (not children)	☐	☐	☐	☐	☐

Through internet social networking

sites (eg Facebook, Twitter, etc)

Please rank on a scale of 1-5 (1=completely agree, 5=completely disagree), how much you agree with the following statements:

Please don't select more than 1 answer(s) per row.

	1 = Completely agree	2 = Agree	3 = Neither agree nor disagree	4 = Disagree	5 = Completely disagree
The people I most often talk to also live close to me					
The people I talk to most often also have a similar education to me					
The people I talk to most often are employed					
The people I talk to most often are also other parents					

How often do the following help you and/or your partner out with childcare?

Please don't select more than 1 answer(s) per row.

	1 = Often	2 = Sometimes	3 = Once or twice	4 = Never
Other relatives				
Friends				
Paid babysitter				
Paid nanny				
Paid daycare				

Do you struggle to find a babysitter and/or childcare?

Please don't select more than 1 answer(s) per row.

	1 = Yes, all the time	2 = Yes, quite often	3 = Sometimes	4 = No, not usually	5 = Not at all
.					

Job searching and career advice

A social networking site is an internet website which allows you to make a personal profile and add content such as pictures or videos. It allows you to connect with other users and view the content that they have uploaded, as well as to view their list of connections (or 'friends').

Examples of such sites are Facebook, Twitter, Instagram and LinkedIn.

These examples do not include apps such as WhatsApp or Yik Yak, where users don't have a profile.

If you have used any of these sources to look up information regarding **educational or career training**, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very useful	2 - Useful	3 - Somewhat useful	4 - Not useful	5 - Not useful at all	6 - Never used
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
Career advice websites (eg Prospects.ac.uk or	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐

scotcareers.co.uk)

Career advisor (in person)

Training company websites (eg skillstraininguk.com)

Educational provider websites (Universities/Colleges)

Asked someone you know through a social networking

site

Newsletters you have subscribed to online

Newspapers or magazines

Advice from a parenting charity (eg One Parent Families

Scotland)

Asked someone you know (not through a social

networking site)

If you have used any of these resources to **help you find a job**, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very		3 -	4 - Not	5 - Not	6 - Never
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐

	useful	2 - Useful	Somewhat useful	useful	useful at all	used
Newspaper adverts						
Jobcentre or other career advisors						
Asked someone you know through a social networking site						
Job listing websites (eg reed.co.uk or 'Universal Jobmatch' at gov.uk/jobsearch)						
Contacting potential employers						
Career advice websites (eg Prospects.ac.uk or scotcareers.co.uk)						
Asked someone you know (not through a social networking site)						

Think about 3 people that you would be most likely to ask for advice from regarding your own career. **For each person, please select the option that best describes your relationship with them:**

	Relationship with person										
	Partner	Close family member	Other family member	Close friend	Someone you know from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Parent of your child(s) friend	Other
Person 1											
Person 2											
Person 3											

Online activity

Where do you use the internet, and how often?

Please don't select more than 1 answer(s) per row.

	More than once a day	Once every day or two	Once a week	Once a Month	Longer than one Month ago, or do not use
At home					
At work/college/uni					
On the move (mobile data connection)					
At friends'/partner's home					
Public WiFi - places such as bars, libraries, coffee shops					

What kind of devices do you use to access the internet regularly (at least once per week)? **Please select all that apply:**

- Your own PC or laptop

- A PC or laptop at work/college/uni

- Someone else's PC or laptop

- Your own smartphone/tablet

- Someone else's smartphone/tablet

Please rate how well you would say you understand the following terms mean on a scale of 1-5? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 - Completely understand	2 - Mostly understand	3 - Somewhat understand	4 - Do not really understand	5 - Do not understand at all
Cookies					
Search engine					
Phishing					
URL					
Upload					

How regularly do you perform the following activities on the internet? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	Regularly (daily/weekly)	Semi-regularly (Monthly)	Sometimes (1-2 times per Year)	Never
Look up job vacancies	☐	☐	☐	☐
Find career advice	☐	☐	☐	☐
Watch movies/TV programmes or sport	☐	☐	☐	☐
Research educational or vocational course information	☐	☐	☐	☐
Research financial information	☐	☐	☐	☐
Shopping	☐	☐	☐	☐
Research health-related information for you or your child(ren)	☐	☐	☐	☐

Read news	☐	☐	☐	☐
	☐	☐	☐	☐
	☐	☐	☐	☐

Play games

Research information on children/childcare

Your social networking site membership

A social networking site is an internet website which allows you to make a personal profile and add content such as pictures or videos. It allows you to connect with other users and view the content that they have uploaded, as well as to view their list of connections (or 'friends').

Examples of such sites are Facebook, Twitter, Instagram and LinkedIn.

These examples do not include apps such as WhatsApp or Yik Yak, where users don't have a profile.

Do you have a profile on, or are you a member of **any** social networking site?

○ Yes

○ No

Your social networking site usage

Which social networking sites do you use, and how often?

Please don't select more than 1 answer(s) per row.

	Always using it	Use once every day or two	Use once a week	Use once a Month	Have an account, but do not use it	Have never used
Facebook						
Twitter						
LinkedIn						
Google+						
Pinterest						
Instagram						
Tumblr						
Other						

Which type of person do you think the following social networking sites are best for keeping in touch with? **Please select all that apply:**

	Don't use this site/not applicable	Partner	Close family member	Other family member	Close friend	Someone from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Other
Facebook	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Twitter	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
LinkedIn	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Google+	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Pinterest	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Instagram	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Tumblr	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Other	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Your social networking site usage

Imagine that you **did not use** any social networking sites. For **each type** of person please rate on a scale of 1-5 whether it would be easier or more difficult to maintain the levels of contact that you currently have. **Please place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 = Very easy to maintain current levels of contact	2 = Quite easy to maintain current levels of contact	3 = It would not make a difference	4 = Quite hard to maintain current levels of contact	5 = Very hard to maintain current levels of contact
Partner					
Close family member					
Other family member					
Close friend					
Someone from school/college/uni					
Work colleague					
Distant friend/acquaintance					
Friend of a friend					
Friend of a family member					
Other					

Certain types of social relationships are more useful for getting different types of information from. What types of people (if any) have you received information from through a social networking site for the below list of topics?

	Never requested help/information via a social networking site	Partner	Close family member	Other family member	Close friend	Someone from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Parent of your child(s) friend
A job vacancy											
An educational or vocational course											
Your current/last job											
Membership of an organisation											
Finance											
Your health											
The internet											

	◻	◻	◻	◻	◻	◻	◻	◻	◻	◻	◻
or computers											

Have you ever used a social networking site profile to try and further your career (for example to promote yourself to potential employers)?

◌ Yes

◌ No

◌ Considering doing so in the future

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If relevant, please briefly explain what you did through your social networking site profile(s), or intend to do in the future:

Prize draw entry

If you would like to be entered into our prize draw please enter your email address in the box below so that we can contact you if you have won 1 of

10 £20 Amazon vouchers.

Email address:

Finished

Thank you for taking part in our survey. Your answers have been recorded.

Key for selection options

1 - Please indicate that you have read and understood the above text, and are happy to continue on to the survey by selecting 'yes'. If you are not happy to continue on to the survey for any reason, please select 'no'.

Yes

No

2 - Are you a parent or guardian of a primary school-age child?

Yes

No

14 - How many children are you the parent or guardian of?

1

2

3

4

5 or more

Appendix 1c: Redundancy survey

Internet and careers - redundancy

Introduction

Thank you for agreeing to take part in our survey.

We are interested in people's experience of redundancy, their attempts to get back into work and any internet use in relation to these.

The following survey will ask you basic questions about your background, and your experiences of using the internet and other sources to find out information which may benefit your career.

Your responses to the questions asked in this survey will be anonymous and the data will be stored electronically in strict confidence. Only anonymous and aggregated data will be reported in subsequent publications.

Your participation in the survey is entirely voluntary and you are free to withdraw from answering the questions at any point. You are not able to save your answers and return to the same point later on (e.g. half way through the survey).

If you are not happy to give a response to a particular question, you may leave it blank and move on to the next. A couple of questions require responses purely to skip you past questions that are not relevant to you. Once your responses have been submitted, these cannot be withdrawn.

If you enter your email address when asked at the end of the survey you will be entered into a prize draw to win 1 of 10 £20 Amazon vouchers. Winners will be contacted once the survey has closed in late Spring 2017. Your email address is not linked to any of your other survey answers, and will only be used to contact you if you have won a voucher.

This survey contributes to a study co-funded by Skills Development Scotland and the Economic and Social Research Council. For further information please contact the project lead researcher:

Kane Needham, 4S24 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 07791558737. EMAIL: kane.needham@stir.ac.uk

Kane is carrying out the survey under supervision of Dr Dave Griffiths. If you wish to make any further enquiries or a complaint Dave's address is:

3S6 Colin Bell Building, Faculty of Social Sciences, University of Stirling, Stirling, FK9 4LA. TEL: 01786 467729. EMAIL: david.griffiths@stir.ac.uk

Please indicate that you have read and understood the above text, and are happy to continue on to the survey by selecting 'yes'. If you are not happy to continue on to the survey for any reason, please select 'no'. *Required*

1/24

Redundancy

Have you been made redundant from a job in the last 3 years? *Required*

- Yes
- No

Your details

Which of the following best describes your gender?

- Male
- Female

What age are you?

Which of these best describes your ethnicity?

- White UK
- White other

- Mixed ethnic groups
- Asian, Asian Scottish or Asian British
- African
- Caribbean or Black
- Other ethnic group
- Prefer not to say

Could you describe what language you usually use?

- English is my first language and is the one I use all the time
- My first language is not English but I speak English all or nearly all the time
- My first language is not English and I speak a different language regularly (e.g. with family at home)
- Other/prefer not to say

Your details

Which of these best describes the area in which you live?

- I live within a city or large town (e.g. population of at least 10,000)
- I live in a small town, village or other area - but I am close to a city or large town (e.g. within 5 miles)
- I live in a small town, village or other area - and am more than 5 miles away from a city or large town

What is the highest level of qualification that you have achieved, or are currently studying for?

- University
- Other post-secondary education (i.e. after mandatory education, but did not go to University)
- Secondary education (i.e. high school)

Which best describes where you live at the moment?

3

- I live in a property that I own outright
- I live in a property that I own with a mortgage
- I rent from a private landlord
- I rent from a local authority/social housing
- Other

How many other people live with you at the moment?

- I live alone
- 1
- 2
- 3
- 4

○ 5 or more other people live with me

Your details

Which of these best describes your **Mother's** highest level of education?

- University
- Other post-secondary education (i.e. after mandatory education, but did not go to University)
- Secondary education (ie high school)
- Don't know/unsure
- Not applicable/did not have relationship with Mother

Which of these best describes your **Father's** highest level of education?

- University
- Other post-secondary education (i.e. after mandatory education, but did not go to University)
- Secondary education (ie high school)

○ Don't know/unsure

○ Not applicable/did not have relationship with Father

Do you currently live with a partner? *Required*

○ Yes

○ No

Your partner

Is your partner currently employed?

- ◌ Yes
- ◌ No

And, if your partner is employed, what is their job title? **Please try and be as specific as possible -** eg if your partner is an 'administrator', state which industry and department they work in:

Redundancy details

Can you confirm which, if any, of the following services you received from PACE partners such as Skills Development Scotland, Jobcentre Plus, or

The Scottish Redundancy Helpline or website? **Please tick all that apply:**

- ☐ PACE presentation and information pack
- ☐ Careers guidance services
- ☐ Information about funding for training
- ☐ Benefits information
- ☐ Financial Services Authority money management information
- ☐ Help with CVs / applications / letters
- ☐ Help with interviews / job search strategies
- ☐ Advice on business start-up
- ☐ None of the above/unsure
- ☐ Other

If you selected Other, please specify:

Roughly when in the last 3 years were you made redundant from your job?

Was this the first time that you had experienced being made redundant? *Required*

- Yes
- No

Redundancy note

If you have been made redundant from a job **more than once** in the last 3 years please refer to **the last time you were made redundant** in the next section.

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Your employment - redundancy

Please answer the following questions regarding **the job that you were made redundant from in the last 3 years in as much detail as possible:**

What did the company/organisation that you worked for mainly make or do?

More info

What was the title of this job?

More info

What did you mainly do in this job? **Please give a brief list of your main duties:**

More info

Which of these did the income from your last job **before tax** fall into:

- £1 - £4,999
- £5,000 - £10,999
- £11,000 - £15,999
- £16,000 - £21,999
- £22,000 - £29,999

- £30,000 - £39,999
- £40,000 - £49,999
- £50,000+

And on average how many hours per week did you work in this job?

- 1-16 hours (part-time)
- 17-34 hours (part-time)
- 35+ hours (full-time)

Post-redundancy employment

Have you had a job since being made redundant in the last 3 years? *Required*

- ◯ Yes
- ◯ No

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Post-redundancy employment - details

Please answer the following questions regarding the job that you **secured following experiencing redundancy** in as much detail as possible**:**

What does the company/organisation that you work(ed) for mainly make or do?

More info

What was the title of this job?

More info

What did you mainly do in this job? **Please give a brief list of your main duties:**

More info

Did you need to complete any additional training/educational qualifications to secure this job?

- Yes
- No

Roughly how long since being made redundant did you secure this job?

○ Less than 3 months

○ 3-6 months

○ 6-12 months

○ 12-18 months

○ 18 months - 2 years

And on average how many hours per week did you work in this job?

○ 1-16 hours (part-time)

○ 17-34 hours (part-time)

○ 35+ hours (full-time)

Which of these did the income from your last job **before tax** fall into:

- £1 - £4,999
- £5,000 - £10,999
- £11,000 - £15,999
- £16,000 - £21,999
- £22,000 - £29,999
- £30,000 - £39,999
- £40,000 - £49,999
- £50,000+

Your social networks and support

The following questions ask about any support that you received from **your social network** following your experience of being made redundant.

Your social network consists of the people that you know - for example close or distant relatives, friends, or people that you work with/used to work with.

If you have experienced redundancy more than once, please answer the questions in relation to **your most recent experience:**

Please rank on a scale of 1-5 (1=completely agree, 5=completely disagree), how much you agree with the following statements:

Please don't select more than 1 answer(s) per row.

	1 = Completely agree	2 = Agree	3 = Neither agree nor disagree	4 = Disagree	5 = Completely disagree
The people I talked to most often also lived close to me					
The people I talked to most often also had a similar education to me					
The people I talked to most often were employed					
The people I talked to most often					

were current/past work colleagues					

Please rank on a scale of 1-5 (1=completely agree, 5=completely disagree), how much you agree with the following statements:

Please don't select more than 1 answer(s) per row.

	1 = Completely agree	2 = Agree	3 = Neither agree nor disagree	4 = Disagree	5 = Completely disagree
I felt I had lots of people that I could gain support or advice from after being made redundant					
After being made redundant I struggled to maintain a daily routine					
After being made redundant I felt more alone as time wore on					

How likely are you to meet new friends these days through the following? Please rank each 1-5 (1=very likely, 5=not likely at all):

Please don't select more than 1 answer(s) per row.

	1 = Very likely	2 = Likely	3 = Sometimes	4 = Not likely	5 = Not likely at all	0 = Not applicable
Through work						
Through volunteering						
Through community organisations						
Through redundancy support programmes (eg PACE)						
Through hobbies						
Through nights out						
Through employment support programmes (eg Jobcentre courses)						

Through your family	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐

Through internet social networking sites (eg Facebook,

Twitter, etc)

Job searching and career advice

A social networking site is an internet website which allows you to make a personal profile and add content such as pictures or videos. It allows you to connect with other users and view the content that they have uploaded, as well as to view their list of connections (or 'friends').

Examples of such sites are Facebook, Twitter, Instagram and LinkedIn.

These examples do not include apps such as WhatsApp or Yik Yak, where users don't have a profile.

If you have used any of these sources to look up information regarding educational or career training, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very useful	2 - Useful	3 - Somewhat useful	4 - Not useful	5 - Not useful at all	6 - Never used
Career advice websites (eg Prospects.ac.uk or scotcareers.co.uk)	☐	☐	☐	☐	☐	☐
Career advisor (in person)	☐	☐	☐	☐	☐	☐
Training company websites (eg skillstraininguk.com)	☐	☐	☐	☐	☐	☐

Educational provider websites (Universities/Colleges)

Asked someone you know through a social networking

site

Newsletters you have subscribed to online

Newspapers or magazines

Advice from an employment charity/organisation (eg

Skills Development Scotland)

Asked someone you know (not through a social

networking site)

If you have used any of these resources to help you find a job, please rate how useful you found them on a scale of 1-5:

Please don't select more than 1 answer(s) per row.

	1 - Very		3 -	4 - Not	5 - Not	6 - Never

	useful	2 - Useful	Somewhat useful	useful	useful at all	used
Newspaper adverts						
Jobcentre or other career advisors						
Asked someone you know through a social networking site						
Job listing websites (eg reed.co.uk or 'Universal Jobmatch' at gov.uk/jobsearch)						
Contacting potential employers						
Career advice websites (eg Prospects.ac.uk or scotcareers.co.uk)						
Asked someone you know (not through a social networking site)						

Think about 3 people that you would be most likely to ask for advice from regarding your own career. **For each person, please select the option that best describes your relationship with them:**

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	Relationship with person									
	Partner	Close family member	Other family member	Close friend	Someone you know from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Other
Person 1										
Person 2										
Person 3										

Online activity

Where do you use the internet, and how often?

Please don't select more than 1 answer(s) per row.

	More than once a day	Once every day or two	Once a week	Once a Month	Longer than one Month ago, or do not use
At home					
At work					
On the move (mobile data connection)					
At friends'/partner's home					
Public WiFi - places such as bars, libraries, coffee shops					

What kind of devices do you use to access the internet regularly (at least once per week)? **Please select all that apply:**

- Your own PC or laptop

- [ ] A PC or laptop at work

- [ ] Someone else's PC or laptop

- [ ] Your own smartphone/tablet

- [ ] Someone else's smartphone/tablet

Please rate how well you would say you **understand what the following terms mean** on a scale of 1-5? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 - Completely understand	2 - Mostly understand	3 - Somewhat understand	4 - Do not really understand	5 - Do not understand at all
Cookies					
Search engine					
Phishing					
URL					
Upload					

How regularly do you perform the following activities on the **internet**? **Place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	Regularly (daily/weekly)	Semi-regularly (Monthly)	Sometimes (1-2 times per Year)	Never
Look up job vacancies				
Find career advice				
Watch movies/TV programmes or sport				
Research educational or vocational course information				
Research financial information				
Shopping				
Research health-related information				

Read news	☐	☐	☐	☐
	☐	☐	☐	☐

Play games

Your social networking site membership

A social networking site is an internet website which allows you to make a personal profile and add content such as pictures or videos. It allows you to connect with other users and view the content that they have uploaded, as well as to view their list of connections (or 'friends').

Examples of such sites are Facebook, Twitter, Instagram and LinkedIn.

These examples do not include apps such as WhatsApp or Yik Yak, where users don't have a profile.

Do you have a profile on, or are you a member of **any** social networking site? *Required*

- ○ Yes
- ○ No

Your social networking site usage

Which social networking sites do you use, and how often?

Please don't select more than 1 answer(s) per row.

	Always using it	Use once every day or two	Use once a week	Use once a Month	Have an account, but do not use it	Have never used
Facebook						
Twitter						
LinkedIn						
Google+						
Pinterest						
Instagram						
Tumblr						
Other						

Which type of person do you think the following social networking sites are best for keeping in touch with? **Please select all that apply:**

	Don't use this site/not applicable	Partner	Close family member	Other family member	Close friend	Someone from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Other
Facebook											
Twitter											
LinkedIn											
Google+											
Pinterest											
Instagram											
Tumblr											
Other											

Your social networking site usage

Imagine that you **did not use** any social networking sites. For **each type** of person please rate on a scale of 1-5 whether it would be **easier or more difficult** to maintain the levels of contact that you currently have. **Please place a tick in each row:**

Please don't select more than 1 answer(s) per row.

	1 = Very easy to maintain current levels of contact	2 = Quite easy to maintain current levels of contact	3 = It would not make a difference	4 = Quite hard to maintain current levels of contact	5 = Very hard to maintain current levels of contact
Partner					
Close family member					
Other family member					
Close friend					
Someone from school/college/uni					
Work colleague					
Distant friend/acquaintance					
Friend of a friend					
Friend of a family member					
Other					

Certain types of social relationships are more useful for getting different types of information from. What types of people (if any) have you received information from through a social networking site for the below list of topics?

	Never requested help/information via a social networking site	Partner	Close family member	Other family member	Close friend	Someone from school/college/uni	Work colleague	Distant friend/acquaintance	Friend of a friend	Friend of a family member	Other r
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
11job vacancy	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

An

educational

or

vocational

course

Your

current/last

job

Membership

of an

organisation

Finance

Your health

The internet

or

computers

Have you ever used a social networking site profile to try and further your career (for example to promote yourself to potential employers)?

- Yes
- No

○ Considering doing so in the future

21/24

If relevant, please briefly explain what you did through your social networking site profile(s), or intend to do in the future:

Prize draw entry

If you would like to be entered into our prize draw please enter your email address in the box below so that we can contact you if you have won 1 of 10 £20 Amazon vouchers.

Your email address will be deleted from our records once the prize draw has been done.

Email address:

Finished

Thank you for taking part in our survey. Your answers have been recorded.

Key for selection options

1 - Please indicate that you have read and understood the above text, and are happy to continue on to the survey by selecting 'yes'. If you are not happy to continue on to the survey for any reason, please select 'no'.

Yes

No

16 - Roughly when in the last 3 years were you made redundant from your job?

In the last 3 months

3-6 months ago

6 months - 1 year ago

Between 1-2 years ago

Between 2-3 years ago

Appendix 2: Ethical approval (original letter located: https://github.com/kaneneedham/PhD-Utility-of-SNS-within-career-management)

Kane Needham

Faculty of Social Sciences

University of Stirling

Stirling FK9 4LA

19/12/2016

Dear Kane

Re: Ethics Application: The role of social networking sites (SNS) in career management skills (CMS). (GUEP 41)

I am pleased to confirm that GUEP has approved your above application. Please note that should any of your proposal change, a further submission (amendment) to GUEP will be necessary.

If you have any further concerns or queries, please do not hesitate to contact the Committee by email to guep@stir.ac.uk.

Yours sincerely,

Pp

On behalf of GUEP

Professor Helen Cheyne

Deputy Chair of GUEP

Appendix 3: Botnet identification

The following output is a data visualisation based upon calculations which helped identify fraudulent responses to the Mothers survey. It separates human and 'bot' responses by timestamps of survey submission. Further documents, including Stata '.do' files detailing how responses are separated can be downloaded at: https://github.com/kaneneedham/PhD-Utility-of-SNS-within-career-management