

Internet Addiction Studies

A Multiple Correspondence Analysis (MCA) of
Research Articles Between 2000 and 2013

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Summary

In this thesis, I conduct a *Multiple Correspondence Analysis* (MCA) on a set of 206 research articles on *Internet Addiction* (IA). To begin with, in section 1, I introduce the background, rationale, theoretical approach, method, and aim to investigate the field of IA research from a *Sociology of Scientific Knowledge* (SSK) perspective. Next, I stipulate two research questions: (RQ1) what constellations of theoretical approaches, methods, geography, and time can be found in IA research? and (RQ2) what do the constellations found in RQ1 say about IA research from a SSK perspective? In section 3, Theory, I therefore outline my theoretical rooting in the SSK in the *Strong Programme* for the study of scientific knowledge, followed by a description of the SSK itself and previous research that takes these theoretical approaches as its starting point. I then focus specifically on the IA research field's relationship with the paradigmatic history of the DSM and the concept of behavioral addictions, which sets the stage for my subsequent operationalization of IA studies in the categories *Biometric*, *Psychometric*, and *Sociological* IA studies. In section 4, Data, Code Scheme and Methods, I outline the data collection in terms of four phases of article exclusion, followed by a description of the methods and code scheme I used to code and analyze my data: content analysis and MCA. In addition, I discuss the ethical standpoints I have taken. In section 5, Results, I present the results of my study using a series of diagrams and bi-plots, which are then discussed in section 6. In short, I conclude that the state of IA research is best described as Normal science, with the caveat that the controversy of the IA concept may indicate that the field is in fact so polarized, scientists in the field may not even use the same terms.

Key Words

Internet Addiction, IA, Multiple Correspondence Analysis, MCA, Diagnostic and Statistical Manual of Mental Disorders, DSM, Strong Programme, Sociology of Scientific Knowledge, SSK, Normal Science, Extraordinary Science, Scientific Intellectual Movement, SIM.

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1. Introduction

In light of the inclusion of non-substance related addictions in the fifth edition of the *American Psychiatric Association's (APA's) Diagnostic and Statistical Manual of Mental Disorders* (APA, 2013), *Internet Addiction (IA)* stands on the doorstep of being classified as a mental disorder. Such a classification, however, has been set on hold until further evidence can corroborate its ontology.

Indeed, the IA concept itself is surrounded by a widespread debate, not only within academia but among the public as well (see for example, Belluck, 1996; Curtis, 2012; Slaton, 2012; Shlam & Medalia, 2014; Scott, 2014). In addition, the classification of Internet use as addictive could have important implications both with respect to social policies aimed at regulating the prevalence of Internet use, and the various interventions that are currently available for the treatment of IA (see for example netaddiction.com; helpguide.com; netaddictionrecovery.com; brmc.com). The classification of IA as a legitimate non-substance related mental disorder could, for example, entail the investment of funding in IA treatment programs and legislative measures enabling enrollment for *Internet Addicts (IAs)* into such treatments. It is therefore important to examine the characteristics of the body of IA research that will serve as evidence in the eventual decision to classify IA as a mental disorder.

IA researchers can be divided into two groups: those who study the symptoms of mental disorders using biometric data and those who make use of psychometric and sociological data (as is done in the DSM 5). A key difference between these branches of IA research is that they produce scientific knowledge using distinct methods and theoretical approaches: they observe different types of evidence using different measurement tools and belong to varying, albeit likely overlapping, scientific communities. While the first group relies upon medical instruments, such as *Magnetic Resonance Imaging (MRI)* scans (see for example Ding et. al., 2013; Hong et. al., 2013), the second uses self-reported psychometric and sociological measurement instruments gathered using statistical survey and interview methods (see for example Romano et. al., 2013; Khazaal et. al., 2011; Khazaal et. al., 2012; Lopez-Fernandez, 2013; Barke et. al., 2012; Hawi, 2013).

Despite these differences, however, one characteristic they do share is a focus on finding symptoms that indicate IA in an individual. This focus on diagnosing IA, rather than explaining it causally, has its roots in the paradigm shift from psychoanalytic approaches to those of clinical and pharmaceutical psychology, which culminated with the publication of the DSM-3 in 1980. Contemporary psychoanalysts were unable to cope with a rapidly growing patient population, caused both by an influx of *Government Issue* (G.I.) veterans from WWII and the de-institutionalization of contemporary mental health care programs. Furthermore, they could not deliver the measurable treatment results required by pharmaceutical companies and faced political criticisms of the psychoanalytic approach (in particular its classification of homosexuality as a mental disorder). Thus, a combination of paradigmatic conflict and developments exogenic to the scientific communities in question shifted the aims of psychiatric practice from that of explaining the causes of mental disorders towards reliably diagnosing them, and ushered forth the type of diagnostically oriented IA research we have today (Strand, 2011; Mayes & Horwitz, 2005).

To explain the shift from one paradigm to another in terms of circumstances that are exogenic to the philosophical development of a scientific concept is in accordance with the *Strong Programme* and its adherents in the *Sociology of Scientific Knowledge* (SSK) for the study of scientific knowledge production (see Bloor, 1976; Kuhn, 1962; Frickel & Gross, 2005). In short, the Strong Programme prescribes a scientific, rather than philosophical, approach to the study of scientific concepts and fields of research, such as IA. The fact that scientific knowledge is a product of a community of researchers working in tandem to produce scientific products: articles, academic degrees, books, talks, political decisions, and so forth, determines the character of its concepts, including that of the scientific method itself.

In conclusion, the aim of this thesis is therefore to investigate the field of IA research from a SSK perspective, i.e. to outline the variation (or lack of such) that can be found historically in the scientific practices of scientists conducting IA studies, and to consider the role that these practices play in the classification and treatment of IA. In particular, I will focus on the methods and theoretical approaches used by IA researchers in empirical studies on IA, along with other indicators of the characters of a scientific community: geographic location of the IA studies, and time.

2. Purpose of the Study

In light of the aim of this study: to investigate the field of *Internet Addiction* (IA) research from a *Sociology of Scientific Knowledge* (SSK) perspective, and my particular focus on the theoretical approaches, methods, geographic location, and chronology of IA research, I pose the following two research questions.

RQ1: What constellations of theoretical approaches, methods, geography, and time can be found in IA research?

RQ2: What do the constellations found in RQ1 say about IA research from a Sociology of Scientific Knowledge (SSK) perspective?

In order to address these research questions, I have gathered a data set consisting of 206 (174 after missing value exclusion) IA research articles published between 2000 and 2013, which I will analyze using *Multivariate Correspondence Analysis* (MCA): a statistical method that can be used to map the (dis)similarity of variable characteristics of a social field (which I will clarify in the section 4.4 below).

3. Theory & Previous Research

In section 2 above, I stipulated two research questions: on the one hand, to investigate the theoretical approaches, methods, geography, and chronology of IA research and, on the other, to analyze the results of this investigation from a *Sociology of Scientific Knowledge* (SSK) perspective. In short, I am thus working under the assumption that the formation of the *Internet Addiction* (IA) concept, and its possible classification as a mental disorder, occurs in a number of social processes that are dependent on the social conditions that precluded it in the scientific community where it was formed.

In the following sections, I clarify this theoretical rooting in the *Strong Programme* and SSK. First, I will detail the Strong Programme as it is stipulated by Bloor (1976) in *Knowledge and Social Imagery*. Second, I will discuss the SSKs implementation of the Strong Programme in terms of *Normal* and *Extraordinary* science (Kuhn, 1962) and *Scientific Intellectual Movements* (SIMs) (Frickel & Gross, 2005), and contrast these

with the classical conceptualization of scientific progress. Next, I will set the stage for my empirical investigation with a discussion on the historical paradigmatic development of the DSM and a discussion on the IA concept itself. Finally, I will stipulate the operationalizations of biometric, psychometric, and sociological IA studies that I used during my data collection.

In sum, the following sections will outline my theoretical rooting in the SSK and set the stage for my subsequent empirical investigation of the IA research field.

3.1 The Strong Programme for the Study of Scientific Knowledge Production

In *Knowledge and Social Imagery*, Bloor (1976) summarizes the Strong Programme in four foundational propositions:

(1) Causality: it examines the conditions (psychological, social, and cultural) that bring about claims to a certain kind of knowledge.

(2) Impartiality: it examines successful as well as unsuccessful knowledge claims.

(3) Symmetry: the same types of explanations are used for successful and unsuccessful knowledge claims alike.

(4) Reflexivity: it must be applicable to sociology itself.

(Bloor, 1976: 7).

First, in the case of *Causality*, Bloor refers to the Strong Programme's focus on explaining how scientific concepts form and develop sociologically. We do not, for example, merely ask why concept B grew out of concept A theoretically. We also ask “Why then?”; “Why there?”; “By what scientific practices?”; and “By whom”? Questions such as these shift our focus from the study of science in terms of truthful versus false strains of thought towards investigating the social processes wherein they were formed. In other words, we take it upon ourselves to explain the formation of scientific concepts causally.

Second, the Strong Programme remains *Impartial* in the face of the veracity of scientific concepts. It is, for example, interesting for scientists under the Strong Programme to study the theoretical propositions made by medieval scientists, even if they seem blatantly false today, if they help us understand the underlying social processes within which they formed. In other words, because the aim of the Strong Programme is to

explain the formation of scientific knowledge, it disregards truth as a prerequisite for empirical investigation.

Third, an investigation that adheres to the Strong Programme is *Symmetrical* in that its focus on causal factors behind the formation of scientific concepts, and an impartiality between them, entails that the same causal process could have created both true and false concepts. We could, for example, explain both the emergence of Marxist and feminist theory from the same underlying interest based social forces, even if these schools of thought are not always fully compatible.

Fourth, the Strong Programme advocates a *Reflexive* attitude among scientists towards their own practices. The scientific method does therefore not stand above the social processes found in scientific communities but should, instead, be studied in accordance with points one to three above. Scientists are people too, which makes them, their scientific communities, and the results of their labor susceptible to the influence of social phenomena. Consequently, scientists and their work become subject to sociological investigation.

In the wake of Bloor's (1976) propositions above, scientists within the field of the *Sociology of Scientific Knowledge* (SSK) have studied concepts empirically in a method and theoretically diverse range of case studies (see for example Armstrong & Blute, 2010; Shapin, 1995; Stambaugh & Trank, 2010; Shilbury, 2010; Tadajewski, 2008; Ciomaga, 2014; Hine, 2006).

For example, Armstrong & Blute (2010) investigate the prevalence of studies in the SSK itself using article meta data from the Web of Science between the years 1957 and 2007, concluding that the Sociology of Science is still used in contemporary articles. Similarly, Shapin (1995) reviews SSK articles with a focus on the early development of SSK and the challenges its adherents faced while establishing their field, such as the recession of the early 1990s', criticisms of its supposed relativizing of truths, and skepticism as to whether the social components of scientific knowledge production could be corroborated using the historical accounts recorded by scientists, or even via a more detailed scrutiny of the everyday activities of scientists (Shapin, 2014: 292 & 312).

In Stambaugh & Trank's (2010) study on the penetration of institutional research in the textbooks of management studies, we find an example of SSK applied to the type of

historical accounts discussed by Shapin (2014). They base their argument on data found by counting the number of citations and author textbook mentions of a set of articles rooted in institutional theory, and present their results in terms of percent mentions per book and page along with the number of foot/end note mentions (Stambouch & Trank, 2010: 668-669).

Ciomaga's (2014) investigation makes use of citation data from the Web of Science to analyze the processes in which scientists in applied research fields, such as the sociology of sport and management, establish their academic legitimacy by relating their work to social theorists in already established social science fields, concluding that the social theorists Foucault, Bourdieu and Connel are heavily referenced and raising the question whether this close relationship entails that fields of applied research should perhaps not be treated as independent (Ciomaga, 2014: 350). Shilbury (2010), meanwhile, use citation analysis to investigate the same field of research with the purpose of identifying its most influential journals.

Tadajewski (2008) explores the possibility of multi-paradigmatic fields using the case of three articles in the field of management studies, concluding that these nonetheless tend to align themselves along a dominant paradigm due to the bias of the reviewers who determine what articles get published or not (Tadajewski, 2008: 291). Finally, Hine (2006) conducts an ethnographic study on research databases, asking herself questions such as “How do the orderings,” (i.e. the databases, in Hine's case a database detailing the genome of mice), “produce collaboration, trust and data sharing?” (Hine, 2006: 274), with the possible effect of decreasing the relevance of physically spaced laboratories, and concluding that this would not be the case as the laboratory also functions as an organizational nexus, where goal-oriented researchers could be led effectively (Hine, 2006: 293).

Clearly, there is thus much diversity in the objects of study and methods in SSK case studies, which include examples of both bibliometric, review, and ethnographic approaches. In the case of this thesis, I will contribute such a study on the field of IA research. Although it, like the studies described above, makes use of research articles as a source of data, my contribution also implements *Multiple Correspondence Analysis* (MCA) as a method of analyzing the results of my study. With this in mind, we can delve further into the SSK's approach to the study of scientific concepts as components of social practices within scientific communities.

3.2 The Sociology of Scientific Knowledge (SSK): Normal & Extraordinary Science

So far, I have described Bloor's (1976) four foundational propositions for the empirical study of scientific development under the Strong Programme. In this section, I will detail Kuhn's (1962) and Frickel and Gross's (2005) theories on how this development occurs more closely and contrast their views with the classical conceptualization of scientific progress.

The classical conceptualization of scientific progress is commonly taught as the following: science progresses by formulating testable propositions whose veracity can be evaluated using observational evidence:

"In general, we look for a new law by the following process: First we guess it.

audience sniggers

Well don't laugh that's the dreary truth! Then we compute the consequences of the guess to see what, if this is right, to see what it would imply, and then we compare those computation results to nature. Or we say compare to experiment or experience, or compare it directly with observation to see if it works.

If it disagrees with experiment it's wrong.

In that simple statement is the key to science. It doesn't make a difference how beautiful your guess is, it doesn't make a difference how smart you are who made the guess, or what his name is: If it disagrees with experiment, it's wrong. That's all there is to it!"

(Feynman, 1964.)

In the viewpoint proffered by Feynman (1964) above, the progression of science is thus driven by a continuous process of theoretical guessing, analysis, and either corroboration or refutation of the guess. The idea is to produce increasingly fine-tuned theories by discarding those statements and propositions that do not stand up to evidence. This fine tuning is, in turn, made possible either by logical scrutiny of the theory's various components and their overall viability. Do their assumptions match up? Are they consistent? Are they possible empirically? Does the theory constitute an improvement compared to other existing theories and, finally, can its propositions be tested against observable evidence? In addition, the logical scrutiny and testing of a theory requires it to take on certain ontological forms. In short, a scientific theory must somehow lend itself to the scientific testing and falsification of its statements about

empirical reality. In Popper's (1935: 10) words, it must be *falsifiable*, i.e. that the theory can be proven wrong with reference to empirical evidence.

In the social sciences, one of the most common methods of testing falsifiable theoretical statements is the statistical hypothesis test: (1) An observation's deviance from the truth and (2) the distance between two observations' deviance from the truth. In these cases, we achieve falsifiability by saying that if our theory is in fact *not* true, we should find results that do not differ significantly from those we would find at random. Thus, the statistical hypothesis tests allow social scientists to make counterfactual statements about the truth, such as “If A is different from B, it is very unlikely that z is below value y¹”. The general applicability of this principle in a variety of contexts thus allows social scientists to collectively develop and test cumulative theoretical propositions and, ideally, allow the field as a whole to progress over time by formulating increasingly accurate theories. The solution to the problem of making progress in social science becomes one of finding data, formulating and testing theories in terms of commensurable and counterfactual theoretical statements, and the implementation of measurement instruments.

An investigation into the development of IA research that embraced the viewpoint above would, therefore, focus on the various arguments and empirical findings that successively siphoned out the incorrect hypotheses over time. Although such a discussion could contain examples of practical studies and anecdotal stories over how various ideas and findings came to be, it would nonetheless be philosophical rather than empirical. Thus, the scientific method, as it is described above, is treated as the universal method of finding truth, however imperfect the contemporary state of knowledge may be.

However, while this ideal of scientific theoretical progression is constructive and elegant, it has also been criticized (perhaps ironically) for failing to accurately describe the historical development of scientific fields in practice. Scholars in the field of *History of Science* and the SSK have noted that while the scientific method certainly is practiced within particular theoretical frameworks, or *paradigms* (which I will clarify below), these practices are recurrently interrupted by dramatic crises, where the taken for granted fundamental propositions that scientific collectives build their research on

¹The most common threshold values for z are +/- 1.96 (95%) and +/- 2.58 (99%), which are indicated using stars (*s) in regression analysis tables.

are replaced by new ones that are incommensurable to those used in previous research (Kuhn, 1962; Frickel & Gross, 2005).

For example, when Blumer (1969) argued that social phenomena derive from the interactions that people have with objects in their surroundings, including innate objects, generalized others, and other people, he is not building on other sociological approaches that assume that behavior stems from the individual and her attitudes. On the contrary, he is replacing the individual as the basic unit of analysis in sociology with the shared interactions between people and both human and non-human objects. This represents an entirely different way of looking at social phenomena compared to theoretical approaches that focus on the individual, and entails both the use of different methods of data collection and a break with many of the at the time contemporary scientific practices within the discipline.

Consequently, a debate between scientists that adhere to these fundamentally different propositions is unlikely to lead to joint scientific efforts. If there is disagreement about the fundamentals, any discussion about their applications is likely to take on the character of a debate where the parties find themselves at cross-purposes. The resolution of this conflict, therefore, is unlikely to be a product of the scientific method. Thus, the SSK narrows the problem exemplified above down to the proposition that the development of science occurs in a non-linear progression that is driven by socio-cultural phenomena, such as politics, psychological and sociological phenomena, and the practicalities that relate to the material sustenance of scientists and their academic institutions. To the extent that the philosophy of the scientific method influences scientific communities, it does so via such phenomena.

Kuhn (1962) conceptualizes this idea by identifying two main states that a scientific field may find itself in during its development: first, there is *Normal Science*, which denotes periods in a scientific field's development that is similar to the one described by Feynman above. Scientists base their research on the previous achievements within the field, i.e. it is commensurable (Kuhn, 1962: 10). The questions they ask, or in Kuhn's terms the puzzles scientists aim to solve, are guided by a set of rules, conventions and standards for conducting science along with a shared understanding of what is (ir)relevant to the field.

We should note, however, that these shared rules and standards of Normal science are not likely to readily accept creative theoretical novelties. Indeed, the guesses scientists make are not random but commensurable. The fundamentals of the field, such as the definition of what constitutes an *atom, individual, actor interest, class, or social interaction*, are not at stake. Rather, they are treated as givens that branch out into incremental theoretical structures which, in turn, specialize into different sub-fields. In other words, they constitute a *paradigm* that defines what scientists in a particular field can guess, do, and how they do it (Kuhn, 1962: 11).

In particular, Kuhn (1962) outlines three types of activities that scientists working under a shared paradigm engage in: (a) the development of the technological tools necessary for experimentation and observation of data, finding data that concerns predictions derived from the paradigm, and fact gathering, which pertains the expansion of the paradigms applications into ever more specialized areas (Kuhn, 1962: 25-27); (b) experiments that develop “laws”, observations of phenomena that build on the assumptions made in the paradigm (Kuhn, 1962: 28); and (c) the exploration of new fields and applications of the paradigm by formulating propositions and running experiments that expand the paradigm (Kuhn, 1962: 29).

The break with Normal science begins with the repeated and frequent occurrence of the so called *Anomaly*. An Anomaly is a result that cannot be explained by a paradigm. In contrast to the differences we might find between a theory and evidence due to, for example, measurement error, an Anomaly is a finding that contradicts the findings we would expect to find. A Marxist may, for example, find that Capital does *not* accumulate in increasingly fewer hands in a particular economy, Economists may find that actors do *not* always act in their own self-interest, or a Functionalist may observe deviant behaviors that are *not* suppressed by its corrective institutions.

In the event of such findings, tensions form between the scientists working under the paradigm as they attempt to explain, or modify, its theory in order to account for Anomalies. Subsequently, in the event that the Anomalies are particularly prevalent, strike at the fundamentals of a paradigm, or co-occur with counter-paradigmatic forces exogenic to scientific communities², counter-paradigms may arise that aim to replace old schools of thought with new ones (Kuhn, 1962: 68).

²Such as the rise of new political social movements, economic crises, and political decisions concerning the funding of various scientific fields.

The field enters a crisis, where competing paradigms make conflicting claims on what the field is about and how it should be studied. In this state, the rules and assumptions that are required by the old paradigm have been loosened and modified to the point where there is widespread insecurity about what the field is supposed to be about (Kuhn, 1962: 82-83). Importantly, unlike the steady and largely linear change that is captured by the activities of Normal science, the changes that happen in crisis are not necessarily scientific but are rather subject to social processes: They can be political, economic, and psychological phenomena such as ideological disagreements, competition over resources (such as grants and academic positions), and personally rooted conflicts.

Consequently, there can only be a resolution of the conflict when either paradigm is abandoned. The sides in an inter-paradigmatic debate find themselves at cross-purposes, where one side argues for a radical reconstruction of both the fundamental theoretical generalizations of the field (Kuhn, 1962: 85) and its future direction, while the other adheres to the practices of the old paradigm. Because the conflict is about the fundamentals: the practices involved in the research the scientists do, it cannot be resolved using the rules or methods of either paradigm. Change is dramatic and rapid. The proponents of conflicting paradigms live, in Kuhn's words, "in different worlds" (Kuhn, 1962: 159). It is here Kuhn draws an analogy between scientific paradigm shifts like the one described above and political revolutions.

Thus, the field enters the second state proposed by Kuhn (1962): the state of *Extraordinary Science*. The new paradigm's reformulation of a field's fundamentals leads to the rapid development of new puzzles and paths of research in the field, both proactively and retroactively. Old observations are re-interpreted, textbooks are rewritten and with it, the way the history of the field is taught changes.

3.3 Scientific Intellectual Movements (SIMs)

Kuhn's (1962) propositions in the *Structure of Scientific Revolutions* had great influence on subsequent studies in the emerging field of the *Sociology of Scientific Knowledge* (SSK). One such development has come out of the fact that Kuhn did not delve deeply into the details of how scientific revolutions play out in practice. Frickel &

Gross (2005), build on Kuhn's work in their conceptualization of paradigm changes in science using the concept of *Scientific Intellectual Movements* (SIMs).

In taking a leaf out of the books of the study of social movements, Frickel & Gross (2005) view social theories as collective efforts where research programs are formed despite resistance from other practitioners in a scientific or intellectual community (Frickel & Gross, 2005: 206). This formation involves not only theoretical developments, but also practical matters. Indeed, researchers need salaries, status, and a sense that their work reflects their identity as intellectuals. In addition, the theories and data researchers produce need contexts for discussion and intellectual exchange, such as conferences, academic institutions, scientific journals, and networks of researchers who keep it alive through their continuing engagement in the activities that keeps the field moving. Scientific endeavors therefore require both financial resources and a coordinated collective effort by a group of researchers who share common goals and views on what constitutes “good” and “bad” research (Frickel & Gross, 2005: 213-219).

Thus, although Frickel & Gross (2005: 210) do recognize the influence of events such as the discovery of new findings, these are merely one of many reasons that together prelude the emergence of new SIMs. In particular, they propose six additional such conditions: (1) first, in the case of an externally rooted dissatisfaction with the theories of the scientific field in question, there can, for example, arise new SIMs out of political movements, such as Marxism and Feminism in the 20th century.

(2) Second, generational shifts may change the composition of researchers towards groups of researchers who are less vested in old paradigms and more open to new ideas. Indeed, scientists largely depend on the adoption and spread of their ideas in order to further their careers. An idea that is proved wrong would, for obvious reasons, limit these advantages.

(3) The influence of generational shifts may, third, be increased if the experiences of the young conflict with those of the old.

(4) Fourth, experience from different social contexts can yield differing perspectives on what observations mean and, indeed, which observations are important. The influx of researchers who have different social backgrounds compared to those previously in the field can thus influence the emergence of SIMs.

(5) Fifth, theoretical developments in neighboring fields may have reverberations in a field. For example, when Blumer (1969) argued for a shift towards interactionism in the social sciences, he was largely drawing inspiration from Mead's (1934) theoretical propositions in the field of psychology 30 years earlier.

(6) Finally, new research technologies may prompt researchers to need to adapt their theoretical assumptions in order to accommodate to the new type of data that they can now observe. In the 1970s, the development of computers and applications that could rapidly calculate *Singular Value Decompositions* (SVDs) made numeric data analyses previously too complex attainable to social scientists, prompting the development of larger and more complex studies and databases.

In sum, although the emphasis on the scientific method that the official versions of most scientific fields' history does have merit, historical investigations suggest that they often fail to account for the often dramatic and non-scientifically based changes they go through in the event of major paradigm shifts. Instead, Kuhn suggests that scientific fields go through perennial states of Normal and Extraordinary science, bridged by states of crisis and uncertainty about what they are really about. While both Kuhn (1962) and Frickel and Gross (2005) agree that these changes can involve both politics and other psychological factors, the latter elaborate on Kuhn's theory with the concept of SIMs. The emergence of new scientific theories and paradigms are collective endeavors, which involve everything from formulating puzzles that attract the interest of scientists to the material sustenance of their livelihood, journals, and academic institutions.

Consequently, the study of the historical and future developments can and should be rooted in empirical investigations of the production of science under various paradigms in practice. In the case of IA research, for example, a study of the methods and theoretical approaches used by scientists could reveal both that the field has gone through a scientifically revolutionary change or that it has remained in a state of Normal science throughout. In the former situation, for example, we should see evidence of multiple paradigms that employ different methods while, in the latter, these will be similar and stable over time.

3.4 The Diagnostic and Statistical Manual of Mental Disorders (DSM)

The history of the *Diagnostic and Statistical Manual for Mental Disorders* (DSM) follows the historical development of the study of mental disorders during the 19th and 20th centuries. Indeed, the *American Psychiatric Association* (APA) traces its roots as far back as the United States 1840 census, where the mental health variables mania, melancholia, monomania, paresis, dementia, dipsomania, and epilepsy were included. In short, the idea was to screen populations for the prevalence of various mental conditions with the purpose of managing the social problems associated with mental disorders (American Psychiatric Association).

However, following the seminal 1909 talks held by Sigmund Freud at Clark University, the rise of the field of psychoanalysis shifted the focus of mental health research beyond the management of mental illness towards its explanation and treatment using psychotherapy, and culminated with the rapid influx of *Government Issue* (G.I.) patients returning from the second World War. Thus, when the first version of the DSM was published in 1952, its purpose was not primarily to form a basis for statistical analysis but rather to objectify the implicit knowledge base that the psychoanalytic practitioners of the time could use in their treatment of veteran G.I.s. This continued over the course of the 1960s, with the DSM-2 elaborating upon the taxonomies used in the DSM-1 (American Psychiatric Association; Strand, 2011: 288).

At the same time, however, competing psychiatric paradigms increasingly came to challenge the Freudian based approaches used by psychoanalysts. They, albeit more numerous than they had ever been, could not cope with the large number of patient populations in need of treatment. This shifted paradigmatic dominance over the field of mental health towards less Freudian-oriented practitioners, such as social workers and psychiatric nurses, who were prone to focus on diagnoses over causal explanations for mental illnesses, standardize their work and use pharmaceutical tools in their treatments (Strand, 2011: 279).

In addition, the de-institutionalization movement in mental health care along with the implementation of community based mental health in the United States, public criticism of current treatment practices (particularly the classification of homosexuality as a mental disorder), and the demand for measurable diagnostic criteria from

pharmaceutical companies ushered forth dramatic changes in the DSM-3 (Strand, 2011: 281, 282-283, 285-286; Mayes & Horwitz, 2005: 252-256). This is where what Strand (2011: 286) refers to as “the rise of diagnostic psychiatry” began. While the emphasis in psychoanalysis had been to identify the causes of the mental illness, the diagnostic approach emphasizes the identification, and alleviation, of the symptoms of mental illnesses (Strand, 2011: 299). In other words, it does not matter why, for example, patient X became schizophrenic, the importance lies in identifying and alleviating the pathological symptoms that the patient experiences. Indeed, it is here the rising influence of psychiatric practitioners becomes evident: The purpose of the DSM-3 was to provide standardized tools for the practice of mental health treatment in a field divided by theoretical disagreements between psychoanalytic and clinical psychologists and overwhelmed by growing patient populations.

Importantly, although the DSM-3 could not provide a full account of all the various mental disorders that practitioners would encounter, it built a basis for the systematic diagnosing, treatment, and formulation of new mental disorders. Thus, the increased scope of the subsequent DSM-4 and 5 reflects not only progress in the field of psychology but also the expansion of the field of mental health overall. Indeed, from the modest 152 pages of the first DSM, the page count of subsequent editions has risen rapidly from 494 pages in the DSM-2 to 886 in the DSM-4, and finally a total of 957 pages in the most recent DSM-5, indicates a rapid increase in behaviors and symptoms which are considered to be pathological.

In conclusion, the historical development of the DSM along with the changes that have occurred in the field of mental health research depends heavily on the methods and theoretical approaches used by psychologists and psychiatrists to observe and measure mental health conditions. Furthermore, these method and theoretical developments have depended on historical developments exogenous to the field of psychological research, such as growing patient populations and the role of practitioners, such as social workers. Indeed, in the case of IA research, we can see an example of the increasingly broad scope of the DSM along with a focus on the observation and measurement of IA symptoms following the inability of psychoanalytic practitioners to cope with rapidly growing patient populations in the post WWII period.

In the following sections, I will therefore first detail the origins of the IA concept and, second, narrow my own focus towards operationalizing these theoretical approaches and

methods in the categories *biometric*, *psychometric*, and *sociological* IA studies followed by my subsequent content analysis and *Multivariate Correspondence Analysis* (MCA) of IA research.

3.5 Non-Substance Addiction Disorders & Internet Addiction (IA)

As was noted in section 3.4 above, the shift in the DSM-3 from the causal explanation of mental disorders towards diagnosing them, prompted a rapid expansion of the number of possible (and treatable) mental disorders. An example of such are *non-substance-related disorders*, which denote addictive behaviors that cause significant impairment and stress for the user. Although the fifth version of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM 5) primarily refers to pathological gambling as an example of such, it also lists *Internet Addiction* (IA) as a possible classification as such in the future (APA, 2013).

Unlike substance addictions, diagnostic criteria for non-substance-related disorders emphasize the loss of control that subjects feel over behaviors, rather than substances. The idea is that although a non-substance related disorder may not entail the use of chemical substances, it can be diagnosed using behavioral symptoms, such as impulsiveness, sensation seeking, urges and worries concerning the behavior in question, and risk-reward assessments (Potenza, 2011: 145). Furthermore, because behavioral variables are subject to the confounding effects of social context, studies on non-substance-related addictions may include relational variables such as age, education, and geographical location (Potenza, 2011: 144) and the study of various sub-populations, such as adolescents. We should note, however, that despite the recognition of the importance of context in the study of behavioral symptoms of addictions, the theoretical underpinnings of non-substance-related disorders are nonetheless the neurology of the brain (Mayes & Horwitz, 2005: 258). Thus, these types of studies do at times include biometric variables, such as *Magnetic Resonance Imaging* (MRI) (Potenza, 2011: 146).

In the case of IA, the earliest example of a conceptualization of Internet use as a non-substance related type of addictive behavior is Young's (1996; 1998) development of the first IA diagnostic survey instruments. In her 1996 study, Young (1996) investigates the

case of a 43 year old homemaker who uses the Internet excessively. She implements seven criteria of addictive IA use: (1) withdrawal, (2) tolerance, (3) preoccupation with the substance, (4) more frequent use than intended, (5) actions aimed at procuring more of the substance, (6) loss of interest in other activities, and (7) a disregard for the physical and social consequences of the substance use (Young, 1996: 900). A respondent's confirmation that she experiences a significant number of these criteria together indicates that she is indeed addicted to the Internet. Indeed, this turned out to be the case for the 43 year old homemaker, who reported experiencing feelings of depression and irritability during times away from the computer, the cancellation of appointments with friends, negligence of basic chores, such as cleaning and cooking, and conflicts with her family due to her Internet use (Young, 1996: 900-901).

Second, in light of the above findings, Young (1998) took inspiration from contemporary pathological gambling tests and developed one of the first versions of a psychometric IA test: (1) preoccupation with the Internet; (2) Internet provides satisfaction; (3) unsuccessful attempts at decreasing Internet use; (4) feeling moody without Internet use; (5) longer Internet sessions than intended; (6) Internet use damages relationships, jobs, occupation; lying about Internet use; (7) Internet use as escape from dysphoric moods. In addition, she identified six key behavioral variables: (1) time since first using the Internet; (2) hours per week spent online; (3) most commonly used applications; (4) attractiveness of the respective applications; (5) problems caused by Internet use; (6) severity of problems caused by internet use. Finally, respondents who fulfilled five or more of Young's above listed IA criteria were classified as IA dependents for further study. (Young, 1998: 238).

Young's (1996; 1998) initial IA studies prompted a number of subsequent evaluations and adaptations of her original IA criteria. For example, Yen et. al. (2012) make use of the so called *Chen Internet Addiction Scale (CHIAS)*, which assesses five dimensions of IA in a Chinese context (Yen et. al., 2012: 589), Khazaal et. al. (2011) developed and tested the validity of a version translated into arabic (Khazaal et. al., 2011: 2) and French (Khazaal et. al., 2012: 399).

In sum, the non-substance-related IA conceptualization emphasizes the behavioral symptoms of IA, which are measured using psychometric variables included in IA tests. While there are several adaptations of these tests, all retain similarities with the original

test proposed by Young (1996; 1998). With respect to the IA measurement instruments themselves, the studies that make use of these are therefore still comparable.

In conclusion, the conceptualization of IA in contemporary research builds on the definition of non-substance-related disorders, such as pathological gambling. However, while the operational emphasis in IA research thus lies with behavioral symptoms, the theoretical underpinnings of IA are nonetheless the neurology of the brain.

3.6 Theoretical Typification of Internet Addiction (IA) Studies

In the previous sections, I have set the stage for an empirical investigation of the development of the *Internet Addiction* (IA) field of research by focusing on the practices of the scientists who produce knowledge within the field. In particular, I have emphasized the paradigm shift from a focus on causally explaining mental disorders towards diagnosing them, which came with the publication of the third version of the *Diagnostic and Statistical Manual for Mental Disorders* (DSM 3) in 1980.

In addition to the geography and chronology of IA research, my focus is, therefore, also on the theoretical approaches and methods used by IA researchers in the field. In short, what do they observe and how do they observe it? In this section, I will outline three theoretical typifications for IA research: (1) *Biometric*, (2) *Psychological*, and (3) *Sociological* IA studies, which have been the basis for the design of the code scheme used in this study.

3.6.1 Biometric Studies

Biometric *Internet Addiction* (IA) studies focus on increases and decreases in brain activity, commonly in the reward centers, in order to determine the stimulative effects that Internet use has on people (Ding et. al., 2013: 2). The results are then compared between "healthy" and addicted individuals, where IA is usually diagnosed using psychological tests (see for example Hong et. al., 2013: 2). An underlying theoretical assumption behind biometric IA research is the notion that internet addiction belongs to a larger family of impulse control disorders, such as gambling and sex addiction (Hong et. al., 2013: 4-5). A common goal is therefore to measure the effect of IA on an individual's cognitive functioning.

While the measurement of cognitive function may be achieved using a variety of approaches, such as experimental face recognition (He et. al., 2011) and memory tasks (Zhu et. al., 2012) tasks, the most common measurement instrument used in biometric IA studies is *Magnetic Resonance Imaging* (MRI). MRI is the use of brain scanners to measure the electrical activity in various sections of the brain (Ding et. al., 2013: 4). In short, the idea is to compare the brain patterns of people with a baseline scan, which represents a "normal" person (Hong et. al., 2013: 6).

Because biometric IA studies focus entirely on the effect of Internet use on the brain, they tend to make use of small n experimental methods aimed detailing the causal effect of Internet use. Study populations therefore commonly include presumably IA addicted individuals and psychiatrically diagnosed populations who are compared to healthy controls.

3.6.2 Psychological Approaches

Psychological studies, like their MRI counterparts, make the theoretical assumption that the causes of *Internet Addiction* (IA) are rooted in the neurology of the brain. Unlike MRI studies, however, they tend to make use of data gathered via psychometric tests in survey form. Such tests usually include various IA scales, which they then correlate with other measurement instruments that concern psychological disorders such as depression, social anxiety, and disorders such as Autism (See for example Romano et. al., 2013: 2).

Q9: How often do you become defensive or secretive when anyone asks you what you do on-line?

Q10: How often do you block out disturbing thoughts about your life with soothing thoughts of the Internet?

Q11: How often do you find yourself anticipating when you will go on-line again?

Q13: How often do you snap, yell, or act annoyed if someone bothers you while you are on-line?

Q17: How often do you try to cut down the amount of time you spend on-line and fail?

In IA test excerpts 9 to 17 above, we can see a number of questions included in Young's (2014) online IA test. Note how the questions aim to capture behavior that is symptomatic of, rather than causally related, to the addictive component of Internet use. Questions do thus *not* directly concern the biometric characteristics of IAs but behavioral ones, such as irritable and defensive behavior in relation to one's Internet use

and failed attempts at cutting down on one's time online. There are also various elaborations of Young's above discussed IA test based both on slight theoretical alterations and cultural adaptations (see for example Khazaal et. al., 2012; Lopez-Fernandez, 2013; Barke et. al., 2012; Hawi, 2013).

Another characteristic of psychological IA studies is that they single out particular populations, such as grade/high school and college students and people diagnosed with various psychiatric disorders during their respondent sampling. The rationale behind this choice is that because Internet use is treated as a neurological stimuli, environmental and relational variables can be discarded. (Romano et. al., 2013: 2). Consequently, the relatively small sample sizes are adapted to suit experimental or quasi-experimental research designs rather than statistical generalizability throughout social contexts.

A recent development in the psychological type of research is the deconstruction of the concept of IA into various sub categories, such as *Social Networking Site* (SNS), ICQ, Facebook, and online shopping addiction. Thus, the problem formulations in such studies are put in terms of understanding the specific behaviors of people online (Bergmark et. al., 2011., Kuss et. al., 2013: 1). While this study will focus specifically on studies that investigate IA, the basic assumptions of these studies are nonetheless the same.

3.6.3 Sociological Approaches

Sociological explanations for the possibly addictive character of Internet use tend to view *Internet Addictive* (IA'd) behavior as a consequence of ideas, morals, and social relationships (e.g. parental variables). These can be tricky to find as they often dress themselves as psychological studies. Nonetheless, they can be identified by their references to relational variables in their explanation of *Internet Addiction* (IA).

Parental variables, for example, concern the relationship between parents and their children, consequential variables refer to the reaction that people in the addict's surroundings have to her IA, and escapism-related variables relate to a need to escape from social relationships. One complicating factor in this category is that there are several relational variables included in most IA tests.

Young (2014)

Q3: How often do you prefer the excitement of the Internet to intimacy with your partner?

Q4: How often do you form new relationships with fellow on-line users?

Q5: How often do others in your life complain to you about the amount of time you spend on-line?

Q19: How often do you choose to spend more time on-line over going out with others?

Hawi (2013: 204)

Q9: Do you become defensive or secretive when someone asks what you do online?

Q10: Do you block disturbing thoughts about your life with soothing thoughts of the Internet?

Q18: Do you try to hide how long you've been online?

Lopez-Fernandez et. al. (2013: 113)

Q1: When I am not in class, I usually think about Online Video Gaming (OVG) and/or Social Networking Sites (SNS)s (the last time I played or enjoyed my scores or friends, my previous sessions, etc.)

Q6: When I play OVG or visit SNS, I can forget my household chores (making my bed, washing dishes, walking the dog, etc.)

Q9: When I play OVG or visit SNS, other people (parents, brother/s, sister/s, friend/s, etc.) complain about the length of time I spend.

Q17: I have met new people through this kind of entertainments (OVG or SNS).

Q23: I have hidden things I have found out through OVG or SNS.

Q25: I have sometimes preferred OVG or SNS to being with my friends.

Khazaal et. al. (2012: 401)

Q11: Do you neglect your daily obligations (work, school, or family life) because you prefer to go on the Internet?

In the IA test excerpts above, we can see a number of questions included that pertain to the Internet user's relationship to people in her surroundings. The respondent is asked to specify how her Internet use relates to her sexuality and personal relationships. For this reason, I will exclude those from the categorization of relational variables (otherwise, almost all IA studies would be inaccurately classified as Sociological). Instead, a study is defined as relational only if one or more of the study's crucial variables are relational. By crucial, I mean that the variable is discussed directly in the text of the article, rather than being mentioned as a side note or as part of a non-relational constellation of variables.

Note that the key to distinguishing the neurological from the relational studies is to interpret them both as sub-categories of the psychological category. In the former case,

Internet use is treated as a stimuli that, in turn, elicits neurological problems such as depression and sleep deprivation, which causes changes in the brain. In the latter case, Internet use is explained by relational variables such as stigma, loneliness, social anxiety, and escapism.

In sum, the key to distinguishing sociological studies from their psychological "cousins" is to focus on the character of the explanatory variables they associate with IA. Because their focus is on relational variables, their sample sizes are likely to be larger than those found in the biometric and psychometric studies. In addition, it is likely IA tests will be used as dependent, rather than independent, in non-experimental study designs which, due to the supra-individual character of relational variables, will aim for breadth rather than depth.

4. Data, Code Scheme & Methods

In section 2 above, I postulated two research questions. First, to find the constellation of theoretical approaches, methods, geography, and time in *Internet Addiction* (IA) studies and, second, to analyze these findings from a *Sociology of Scientific Knowledge* (SSK) perspective. In order to find a base of data for the former, I have gathered and coded a number of research articles between 2000 and 2013 using the Web of Science and PsycInfo scientific databases using a content analysis aimed at distinguishing the methods used in biometric, psychometric, and sociological studies. Second, I analyzed the data using the *Multiple Correspondence Analysis* (MCA) method, which produces the type of constellations required for an analysis from an SSK perspective, and discussed them further in the discussion (see section 5 below).

4.1 Data

The data used in this study consists both of journal titles and abstracts, which were included if they were deemed empirical, on the topic of *Internet Addiction* (IA), and

available via the Stockholm University library system. Subsequently, a series of readings and data refinement phases produced a number of article inclusions (n=174) and exclusions (n=2000).

4.1.1 Four Phases of Data Exclusion

The data I use in this study were collected in four phases. The first two aimed to identify articles which were both empirical and concerned the *Internet Addiction* (IA) concept. In the third phase, full text versions of the IA articles were read and coded using a series of 31 variables subsumed under five categories (which I will detail in section 4.2 below) and, in the final fourth phase, missing values were excluded from the data in order to enable the use of a *Multiple Correspondence Analysis* (MCA).

Each phase produced a number of article exclusions and inclusions:

(1) In the first phase, a total of 2174 article titles were collected from the Web of Science (n=1873) and the PsycInfo (n=301) databases using the search queries "Internet Addiction" (n=695), "Problematic Internet Use" (n=589), "Compulsive Internet Use" (n=154), "Excessive Internet Use" (n=199), "Pathological Internet Use" (n=201), "Information Technology Addiction" (n=120), "Communication Technology Addiction" (n=57), and "Addictive Internet Use" (n=159). The idea was to formulate a broad set of queries in order to capture the various biometric, psychometric, and sociological studies available on IA (see sections 3.3.1, 3.3.2, and 3.3.3 above). Of these studies, 873 articles could be excluded based on the article titles and 295 lacked available abstracts, which yielded 1006 articles whose abstracts could be read in the second phase.

(2) Next, the abstracts were skimmed in order to identify those articles that were both empirical and concerned the topic of IA. This yielded another 449 exclusions and 56 doubles, which set the sum total of articles available for a full text reading to 501.

(3) In the third phase, consideration had to first be taken to the resource limitations of this study. Articles were therefore sorted chronologically in order to exclude 67 of the oldest articles from the sample. In addition, another 101 doubles and 95 articles without full text access in the Stockholm University library were identified. The readings themselves then generated 32 additional exclusions, leaving the sum total of the data set to 206 articles.

(4) In the fourth phase, the data was coded using a series of 31 categories. This produced another 32 exclusions of articles that contained missing values, which would cause problems in the forthcoming MCA, thus leaving a final sum total of 174 articles for use in the analysis.

In sum, the initial data set comprised of 2174 article titles were reduced to 174 full text articles in a series of four phases. In total, 157 (7%) articles were excluded because they were doubles, 390 (18%) due to a lack of full text access in the Stockholm University library, 67 (3%) of the oldest articles because of the resource limitations of this study, 1354 (62%) because they did not include an empirical investigation of IA, and 32 (2%) because they contained missing values.

4.2 Code Scheme

In total, the full text reading categorized the articles using 31 variables subsumed under five categories: (1) *Publication Details*, (2) *Study Type*, (3) *Sample Traits*, (4) *Measurement*, and (5) *Study Design*.

<u>Publication Details</u>	<u>Sample Traits</u>	<u>Measurement</u>
Author(s)	n size	MRI/Brain Scan
University	Random	Psychological test (dependent)
Year	Quasi Experimental	Psychological test (independent)
Title	Geographical Location	Remote Survey
	Online Sample	Interview
<u>Study Type</u>	Age (+/- s)	<u>Study Design</u>
Biometric	Age (min/max)	Longitudinal
Psychometric	Grade/High School Students	Experimental
Sociological	College Students	Intervention
Prevalence	Psychiatric Disorder	Control Group
Prevalence %		Psychotest Evaluation
		IA Bechmarks
		Consequences

Diagram 1. The Code Schemata for the Full Text Article Analysis

In table 1 above, we can see the operationalization of the methods used in the 206 Internet Addiction articles that were included in the third wave full text reading. To begin with, each article's theoretical underpinnings were categorized as *biometric*,

psychometric or *sociological*. Next, the articles' various sample traits, such as sample size (*n size*), randomness (*Random*) of the data collection, and target groups foci such as students (*Grade/High School* and *College Students*) or specific *Psychiatric Disorder*-groups were identified. Subsequently, the data measurement tactics of the articles were coded, such as *Magnetic Resonance Imaging (MRI) Scans* and *Remote Surveys*, followed by their overall study designs, such as *Experiments* with *Control Groups*, *Intervention* evaluations, and *Longitudinal* data collections.

4.3 Content Analysis

Content analysis is the quantitative analysis of the content of text based communication (Babbie, 2010). The idea is to identify patterns in the material using the meaning of a concept expressed in the form of a set of terms, which can be identified using either computerized algorithms or a manual human reading. However, because the meaning of a piece of written piece of text may vary highly between authors, audiences, and social contexts, it is important to provide a strong argument for why a particular piece of text is included in the analysis or not.

In my case, the inclusion criteria are based on the the fact that the scientific articles in my sample have gone through the so called peer-review process before publication. By this, I mean that they have been reviewed by academics in the field of research where the article is to be presented. Thus, the articles have a clear audience and are likely to adhere to the contextual use of the terms that are used in the IA research fields that are investigated in this study.

A similar problem pertains to the varying meanings scientists may attribute scientific concepts (Armstrong & Blute, 2010: 436), such as the search terms used to gather article titles in phase one of my data collection procedure (see section 4.1.1 above). Although this problem is almost impossible to resolve entirely, the fact that I included only articles that specifically concerned the empirical investigation of IA may at least alleviate this problem in the sense that they concern the same type research goal: to increase empirically based knowledge about IA.

4.4 Multiple Correspondence Analysis (MCA)

*Multiple Correspondence Analysis (MCA)*³ is a statistical method of transforming nominal and ordinal scale data into ratio scale chi-2 distances, or clouds of data points, that can be factorized using a *Singular Value Decomposition (SVD)* (for additional overviews, see Nenadic & Greenacre, 2005; Roux & Rouanet, 2010). Commonly, the resulting eigenvectors and eigenvalues are expressed in the form of two dimensional coordinate systems that reduce the complexity of the data and are illustrated using so called bi-plots, which are scatterplots whose axes correspond to two chosen eigenvalues (usually those that preserve the highest degree of variance of the cloud). The main benefit of this procedure is that it allows us to reduce the complexity of nominal scale data sets, often consisting of dozens or even hundreds of variables, into two dimensional systems of coordinates.

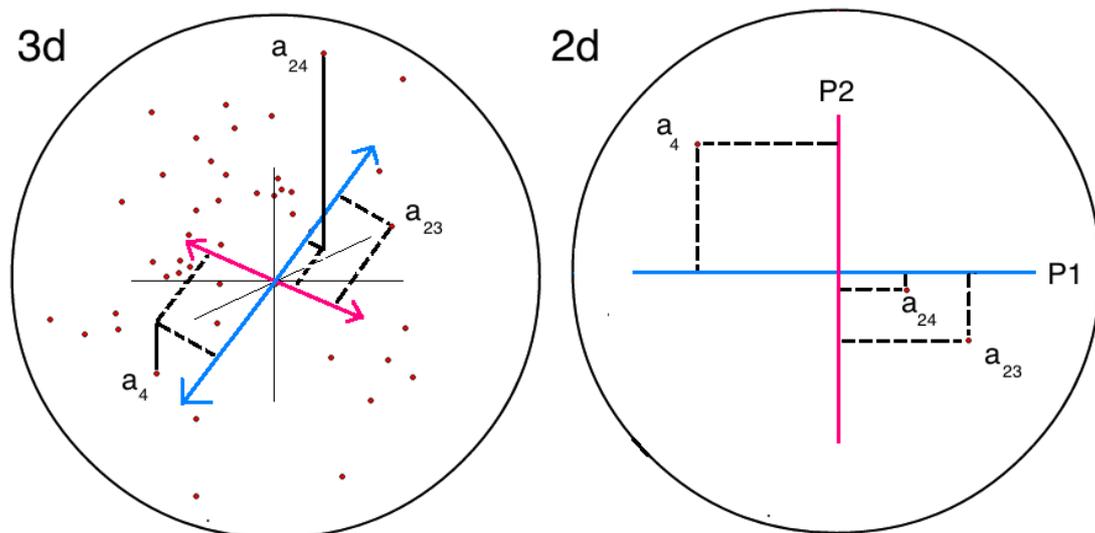


Diagram 2. Example of a Dimensionality Reduction (image to the right) of a Cloud of Points into a Bi-Plot (image to the left).

In diagram 1 above, we can see an illustration of the type of dimensionality reduction that occurs in an MCA. In the image to the left, a cloud of chi-2 distances is dissected by two vectors (pink and blue) that cut through the coordinates in such a way that the total distance between them, or in other words their variance, is maximized. The result is a two-dimensional representation of the cloud (the image to the right) that preserves as much of the cloud's variance as possible while simultaneously reducing the

³*Multiple Correspondence Analysis (MCA)* is at times also referred to as homogeneity analysis, canonical correspondence analysis, multivariate correspondence analysis, and dual scaling.

complexity of the data. In other words, the coordinates in the multidimensional cloud are projected on to a two dimensional plane, whose axes are determined by the the amount of variance that each eigenvector covers⁴.

When analyzing the results of the procedure above, we will observe that patterns which are similar correspond to coordinates that are close to each other and vice versa. In the example above, for example, this means that points a23 and 24 are perceived as being located closer to each other than they are to point a4, even though they seem almost equidistant in the original three dimensional plot (to the left). Although one might protest the loss of detail we get using this procedure, its necessity becomes apparent if we imagine the difficulties we would have interpreting, for example, a 31 dimensional cloud of points.

The key challenge to overcome before the above procedure is possible, however, is expressing our nominal scale variables in terms of ratio scale distances. Indeed, the starting point for an MCA is usually a table containing rows and columns of binary nominal scale data, which is referred to as an *indicator matrix*.

<i>i</i>	<i>A1</i>	<i>A2</i>	<i>B1</i>	<i>B2</i>	<i>Total</i>
1	1	0	1	0	2
2	0	1	1	0	2
3	1	0	1	1	3
4	1	1	0	1	3
Total	3	2	3	2	10

Table 2. An Indicator Matrix Containing Two Variables (A & B) and Four Individuals (i).

In table 2 above, we can see an example of an indicator matrix whose rows represent individuals $i=1$ to $i=4$ and columns represent categories of the variables A and B. Each individual in the matrix may score false = 0 or true =1 values for each of the categories, which together amount to patterns representing each individual through the set of variables included in the data.

The idea is to transform the cell values of indicator matrices into ratio scale chi-2 distances between points in a cloud, whose dimensionality can then be reduced into a selection of the cloud's eigenvectors and values found using a SVD. In order to achieve

⁴It is in this sense a *Multiple Correspondence Analysis* (MCA) is similar to a *Principal Component Analysis* (PCA).

this, the cell values of the categorical data must first be transformed into their distances from their respective expected values:

$$d_{ij} = \frac{(p_{ij} - eP_{ij})}{\sqrt{eP_{ij}}} \text{ where } p_{ij} = \frac{z_{ij}}{N} \text{ and } eP_{ij} = rm_{ij} \cdot cm_{ij}$$

z : The indicator matrix value (0/1) of element ij .

N : The total number of indicator matrix elements with a value of 1.

p : Cell ij 's proportional weight of N .

rm : To total weight of row i .

cm : The total weight of column j .

eP : The expected weight of element ij based on its row and column weights.

In the formula above, we can see the calculations required to transform the categorical data of an indicator matrix into distances (d) from their respective expected values (eP). First, each indicator matrix cell (z) is transformed into its proportional weight of the sum-total of values equal to one. This is referred to as a *Correspondence* matrix (P). Second, the expected weight of the cells, as expressed by the product of their total row and column weights, is subtracted from each proportion. Thus, we get a cloud of points whose barycenter is the expected value of each of the matrice's elements (D). Third, the similarity of the rows (the individuals) and the columns (variable categories) can be analyzed by projecting them onto chosen eigenvalues of the matrix, which we may extract using a SVD. The SVD, in turn, gives us the factorized decomposition of our distance matrix D , including the eigenvectors and eigenvalues required to reduce its dimensionality.

Each eigenvector will explain a share of the total variance of the cloud and the sum total of all their variances covers 100% of the cloud's variance.

$$\lambda_{i\%} = \frac{\lambda_i}{\sum_{i=1}^n \lambda_i} \cdot 100$$

In the formula above, we can see the calculation of the inertia of an eigenvalue. What we are doing is utilizing the fact that the sum of the eigenvalues of a cloud encompasses its entire variation. Therefore, each eigenvalue's share of that total multiplied by 100 corresponds to its percentage of the variance of the cloud. The choice of eigenvectors for use in our bi-plots commonly entails selecting those two dimensions that produce

the highest degree of variance. The sum total of these then becomes the variance that our plot explains.

Finally, we can use the eigenvalues of our two chosen dimensions to identify each *row* (individual's) and *column* (variable category's) position in the bi-plot. Because they thus influence the positioning of the plot's coordinates, the columns that go through this procedure are thenceforth referred to as *active* variables.

$$PI_i = \frac{SI_i}{\sqrt{\lambda_1}} \quad \text{where } SI_i = \frac{u_i \cdot \sqrt{\lambda_1}}{\sqrt{rm_i}}$$

$$PCI_i = SCl_i \cdot \sqrt{\lambda_1} \quad \text{where } SCl_i = \frac{u_i}{\sqrt{cm_i}}$$

In the formulas above, we can see the calculation of the row and column coordinates for an active variable in an MCA. First, the standard row coordinates *SI* are calculated by multiplying individual *i*'s row eigenvector value by the square root of the eigenvalue of our choice, and then expressing the result in terms of the square root of row *i*'s weight (*rm*). Next, *SI* is divided by our chosen eigenvalue, which gives us the principal coordinate (*PI*) of row *i*. A similar procedure is then repeated for the principal column coordinates (*PCI*). Finally, once this procedure has been repeated for the second eigenvalue of choice, we get the coordinates of our bi-plot.

Two characteristics of an active variable serve to set it apart from other variables in the resulting bi-plot coordinate system: (1) the uniqueness of its pattern in the indicator matrix and (2) the scarcity of the individuals who have the variable's characteristic. In other words, the more unique one variable is compared to another, the farther away they will be from each other, and the less common it is, the further away it will be located from origo of the bi-plot.

While, however, this captures the (dis)similarities between variables and individuals that we are looking for in an MCA, outlier variables with particularly few individuals can therefore entail a disproportionate amount of variance in a particular eigenvector, which can cause us to use sub-optimal eigenvalues in our calculations of the bi-plot coordinates. Furthermore, we could feasibly want to include variables that we would not want to include in the calculation of an MCA. One example of such could be time:

While time could play a crucial role in determining the development of a field, we could not say that any particular part of a field would have unique access to it.

The remedy to these problems is the use of so called *supplementary variables*, which allow us to identify the position of a variable without including it in the calculation of the MCA's eigenvectors.

$$SUI_A = \frac{\sum_{i=1}^n (a_i \cdot PI_i)}{\sum_{i=1}^n (a_i)}$$

In the formula above, we can see the calculation of the *first supplementary principal coordinate* (SU1) of variable A. Each positive value of variable A (0/1) is multiplied by the principal coordinate of their respective individual observations. The resulting sum total is then divided by the total number of positive values in the variable, giving us our result. Note that this does *not* require us to include variable A in the original MCA, which means we can exclude its influence on the eigenvalues of our data. The same procedure is then repeated for the *second supplementary principal coordinate* (SU2).

Once we have computed the coordinates of the individual (row), active (column) and supplementary variable (column) clouds, we can analyze their characteristics. Above, I have already pointed out that the distance between the coordinates in the plot tell us something about the similarity of the variables. In addition, we can observe the internal spread of the clouds, i.e. their variance.

$$VAR_{cloudA} = \frac{\sum_{i=1}^n ((PI_{ai} - \bar{PI}_A)^2 + (P2_{ai} - \bar{P2}_A)^2)}{N_A}$$

In the formula above, we can see the calculation of the non-weighted variance for a cloud of coordinates. First, the sum total of each squared distance from the mean first and second coordinates is calculated. Next, this is divided by the total number of coordinates (N) in order to give us the cloud's variance. At this point, we should note that the formula above does *not* take the frequency distribution between the variables into account, i.e. their *weights*. While this would make sense if we were calculating the variance of a cloud in euclidian space, this is not important in our case because we want the uniqueness of a coordinate to depend on said weight (see the calculation of p above).

In other words, I want the fact that a variable is unique due to its rarity to matter, therefore, I will make use of the non-weighted variance in my forthcoming analysis.

4.5 Ethical Considerations

The issue of ethical research practices can be divided into two sub-topics: (1) issues that concern the protection of the individuals observed the field and (2) issues that concern the conduct of the researcher in relation to the stakeholders of one's findings⁵. Because this study does not conduct any observations of individuals in the field, I will focus on the latter.

In their taxonomy over the ethical challenges that allude to Cochrane-style reviews, which are similar to my study, Wager & Wiffen (2011) list six ethical issues that address both the problems of review accuracy and the ethical conduct of included authors. First, one must consider the authorship of the articles included in the review. Who did the work? Sometimes junior authors are pressured by more senior colleagues who, despite having contributed little to the study, insist on being listed among the authors of the article. This is known as *guest authorship*. Conversely, there are the cases where authors who have contributed to the study are left out of the author list entirely, which is known as *ghost authorship* (Wager & Wiffen, 2011: 130). Noting that such problems are very difficult to detect in a systematic review, I can conclude that I have detected no apparent cases of either guest or ghost authorship.

Second, there is the problem of avoiding redundant articles in the review scope. If, for example, the same study is published twice in different journals, the results of a subsequent meta-analysis will yield inaccurate results. Thus, redundant articles may cause bias in a review's results, which, if done consciously, becomes not only a question of validity, but also one of the ethical use of data⁶ (Wager & Wiffen, 2011: 131). In order to avoid the inclusion of redundant articles in my review, I have sorted them first by title, followed by an inspection of studies with identical sample sizes and designs. This, however, revealed no redundant articles in my data.

⁵These include both researchers, practitioners, and the subjects of interventions based on one's study.

⁶This situation could be compared to that of tweaking data in order to manipulate one's results.

Third, because systematic reviews build largely on the results of previous studies, they are at particular risk of plagiarizing the findings and ideas of the articles included in the review. This problem can be alleviated with the careful use of reformulation, citation, and quotation of findings and ideas taken from the articles in the review.

Fourth and fifth, the data collection in systematic reviews is by design based on the subjective evaluations of the readers. Indeed, these inevitably have opinions and experiences of the field of study, which will affect the judgements they make concerning the character and quality of the studies they read on that topic. Although the design of systematic reviews mean that this problem cannot be avoided entirely, it can be alleviated by, in part, stating such sources of bias openly and, in part, by evaluating the concurrence of categorization judgements between several readers (Wager & Wiffen, 2011: 133).

Here we should note that because I am the sole reader in my study, it is susceptible to possible bias caused by my opinions on the topic of IA research. I hope, however, that my theoretical sections above will have provided a sufficient account of my theoretical pre-dispositions.

5. Results

In the sections above, I have taken a *Sociology of Scientific Knowledge* (SSK) approach to the study of *Internet Addiction* (IA) research. This entails a focus on the practices of collectives of scientists laboring to produce knowledge within their fields, which may have the character of the steady progression of Normal science or the crisis and creative flux of Extraordinary science (see sections 3.2-3.3 above) (Kuhn, 1962; Frickel & Gross, 2005). In the following sections, findings that provide indications of the homo/heterogeneity of the field are therefore of particular interest. Furthermore, I will focus on the theoretical approaches, methods, geography, and time of the studies conducted by IA researchers in the field.

In the following sections, I will analyze the results of my study using *Multiple Correspondence Analysis* (MCA), which segments the data into a series of clouds through its eigenvectors (for a methodological overview, see section 4.4). First, in order

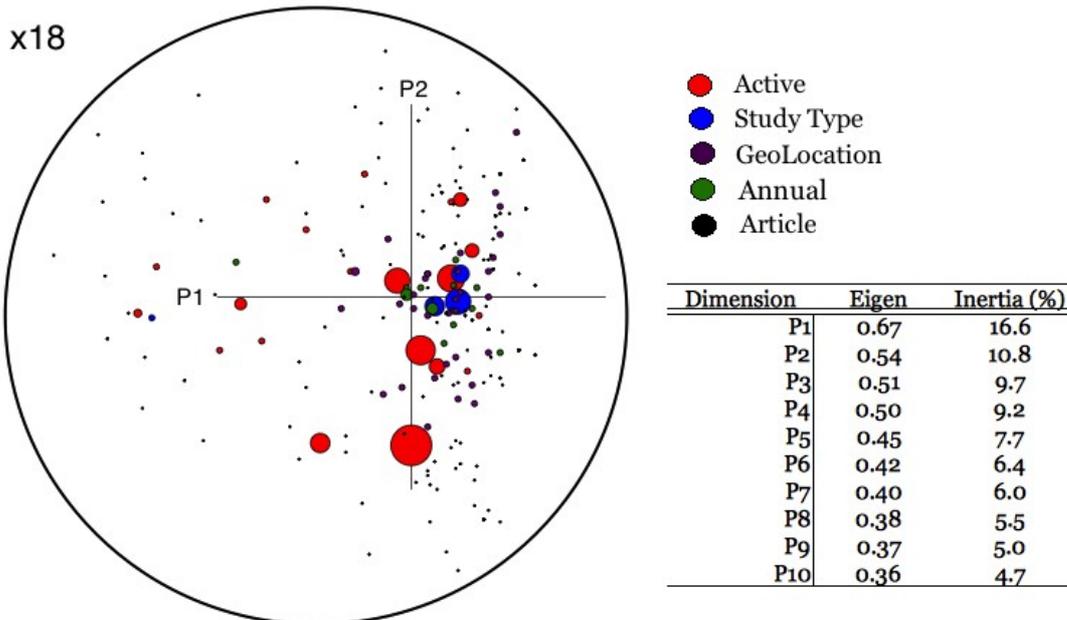
to provide a contextual background to the results, I will present an overview of the data as a whole. There, I will discuss their eigenvalue decomposition and their explained inertias along with comparisons between the cloud's non-weighted sub-cloud variances. Second, I will detail the active variable and study type clouds. Third, I will present a geographical analysis of the field of IA research followed by, fourth, an analysis of the field's development over time.

The analysis includes both active and supplementary variables. In the former case, by “active”, we mean that they have had an influence on the dimensionality reduction in the MCA. In other words, these are the variables that have been used to select P1 and P2 in our bi-plots. In the latter case, by “supplementary”, we mean that the variables (study type, geography, and time) have been projected in the plot without such an influence (for a methodological overview, see section 4.4 above).

Because the results depend largely on visual interpretations, there is also an interactive version of the results that can be found at: <http://einarstenson.se/MA/#/TMCA>. In addition, a non-digital version of these more detailed bi-plots can be found in the form of a series of magnified bi-plots in Appendix 2.

5.1 Total Results, Active & Supplementary Variables

In this section, I will present an overview of the results of the *Multiple Correspondence Analysis* (MCA) by observing the overall clustering of the cloud and the explained inertia of its dimensions. In short, the idea is to provide a comparative baseline that puts the active, study type, geographic location (GeoLocation), and time (annual year) variables, and the articles themselves into a common context, which can serve as a background to the forthcoming more detailed sub-cloud analyses.



Bi-Plot 1. & Table 3. Contextual View of the Field of Internet Addiction (IA) Research. Magnification: 1.05x18; Inertias: P1: 16.6%; P2: 10.8%. n = 174. X: P1; Y: P2.

In bi-plot 1 and table 3 above, we can see the total result of the MCA, which includes active, study type, geographical (geoLocation), annual, and article cloud coordinates. The coordinate system describes the inertia, or in other words the cloud variance contributions, of the first two eigenvalues (P1 & P2). Together, they cover $16.6 + 10.8 = 27.4\%$ of the cloud's total inertia. Furthermore, the inertia between the other dimensions seems evenly distributed, with inertias above 9% down to the fourth dimension. We can thus think of the cloud as more “round” than it is “flat”⁷.

In this initial bi-plot, we can see that the clouds share a common center, with the highest concentration of coordinates and frequencies in the first and fourth quadrants, along with an off-shoot into the third quadrant. This indicates that while most IA articles are similar to each other, there are exceptions which share common and different characteristics. This is interesting because it indicates that there are different types of IA articles, rather than a core surrounded by occasional outlier studies.

Furthermore, the clouds' contributions to the variance of the plot are not equally distributed. Indeed, expressed as non-weighted⁸ cloud contributions, excluding the cloud of articles, the active variables contribute the most ($VAR_{Active} = 0.291$),

⁷Strictly speaking, we cannot speak in terms of “round” or “flat” as our cloud exists in more than three dimensions. Nonetheless, I think the analogy does serve the purpose of underscoring that the cloud shoots off relatively evenly in the direction of the first nine eigenvectors.

⁸In this case, it is better to use the non-weighted contributions as we want the rarity of a variable to have an influence on the results (see section 4.4 above).

(n=154), which is at the opposite end of online samples (n=24) and experimental (n=12) methods in P2. With respect to the measurement instruments used in IA articles, psychoTest (Depend) (n=103), which identifies studies that use test instruments as their dependent variable in regression-style analyses, is relatively close to the use of such tests as independent (n=54).

Upon examining the study populations used in the IA articles, we can see that college students (n=70) are the most common, followed by grade/high school students (n=61). Indeed, upon a closer inspection, 72% (125/174) of the IA articles made use of both or either of these. Interestingly, these greatly surpass the number of studies that use online samples (n=24). In addition, studies that made use of quasi experimental (n=10), longitudinal (n=22), experimental (n=12), intervention (n=9), and interview (n=17) methods and/or control groups (n=21), *Magnetic Resonance Imaging* (MRI) scans (n=11) were more scarce and gravitated towards the biometric approaches in the field's off-shoot.

Next, when we look at the study type variables (green in diagram 2 and blue in Bi-plot 2), we can see that the most common type of IA study is sociological (n=93), which denotes studies that depend on social interaction between people (see section 3.6.3). Following the sociological study type, psychometric studies (n=69) are the second largest category, prevalence (n=63) the third, while biometric studies (n=12) are more scarce. Furthermore, while the sociological, psychometric, and prevalence studies are oriented towards the center of the plot, biometric studies stand out in that they are located in the off-shoot of the field. Indeed, the study type cloud thus displays a binary division between, on the one hand, sociological, prevalence, and psychometric studies, and, on the other, biometric studies.

In the off-shoot of bi-plot 2 above, we can see that biometric study types will tend to implement instrument evaluation, quasi experimental, and longitudinal study designs on small or medium sized samples of IAs with psychiatric disorders. Here, the measurement instrument of choice is MRI. Ding et. al. (2013), for example, compared 17 children aged 14 to 17 years from the Department of Child and Adolescent Psychiatry in the Shanghai Medical Center with 24 healthy controls using *resting state functional Magnetic Resonance Imaging* (fMRI), concluding that the resting state images between the groups were indeed different. Similarly, Yuan et. Al (2011) examine 18 freshman college students and a group of 18 matched healthy controls, concluding

that long term IA could result in white matter brain structural alterations, which could explain the chronic dysfunctions of presumed *Internet Addicts* (IAs). In other words, here, focus is on the direct measurement of biological indicators of IA using medical measurement instruments.

Meanwhile, towards the center of the clouds in bi-plot 2, we can see that sociological, psychometric, and prevalence studies, tend to implement large n studies using random samples with grade/high school children. Andreou & Svoli (2012), for example, study the relationship between the dimensions of the Greek version of the *Internet Addiction Test* (IAT), demographic factors and other psychiatric disorders, such as depression, in a group of 384 Greek grade school adolescents, concluding that there is significant comorbidity between the various disorder types. Similarly, Öztürk & Kaymak-Özmen (2011) investigated comorbidity between the *Problematic Internet Use Scale* (PIUS) and individual characteristics such as shyness and loneliness, and sociological variables such as gender and class, in a population of 453 Turkish college students, concluding that students that chatted and use online games were more prone to *Problematic Internet Use* (PIU). Here, focus is on indirect and statistical indicators of IA in the form of IA test batteries.

In sum, the most common type of IA study design is a sociological, psychometric, and/or prevalence oriented large n remote survey investigation on grade/high school and/or college student populations. In the off-shoot of the field, however, I have observed a number of biometric studies, which tend to make use of small n MRI studies of IAs, populations that have other mental disorders and healthy controls.

5.3 Geographical Dispersion of Contemporary Internet Addiction (IA) Research

In this section, I will present a more detailed account of the relative positions of the geographical locations (geoLocation) of the *Internet Addiction* (IA) articles investigated in this study. In order to better observe their variation, I have zoomed (x28) in on the area that covers their positions using the interactive tool included with the online section of this thesis (see <http://einarstenson.se/MA/#/TMCA>). Note also that unlike the other bi-plots discussed in this section, node sizes are here proportional within the cloud.

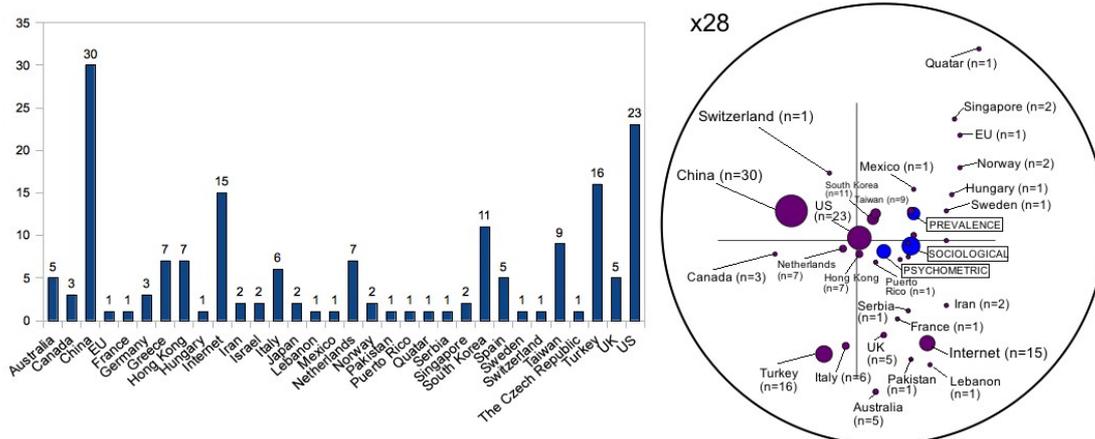


Diagram 4. & Bi-Plot 3. Geographical Location of Internet Addiction (IA) Studies Between 2000 and 2013. Magnification: 1.05*28. Inertias: P1: 16.6%; P2: 10.8%. n = 174. Node Size is Proportional Within the geoLocation Cloud. X: P1; Y: P2.

In diagram 4 and bi-plot 3 above, we can see the frequency distribution and geographical (geoLocation) MCA coordinates of the IA research articles included in this study. To begin with, it is apparent that the highest number of IA articles were located in China (n=30), followed by the United States (n=23) and Turkey (n=16), which together make up 40% of the IA articles. Less frequent are countries such as Sweden (n=1), Hungary (n=1), Norway (n=2), Canada (n=3), and Qatar (n=1). In addition, 15 (9%) articles use populations sampled from the Internet.

Furthermore, the field demonstrates a pattern similar, albeit less pronounced, to those observed in bi-plots 1 and 2 above: There is a clear center around sociological, psychometric, and prevalence studies along with an off-shoot towards biometric studies in the field. In this case, the off-shoot categories are China and Canada, the former which makes up 83% of the biometric IA articles. Turkey, too, stands out in that 68% of its articles are conducted on college student samples. In addition, because China carries so many IA articles, we can see that the center of the geoLocation cloud is less dense than the one observed for the active variables, with 28% of the articles either in the off-shoot or away from the center. Indeed, the center also holds a large number of numerically scarce countries, such as Puerto Rico (n=1), Serbia (n=1), and Mexico (n=1) along with more frequent countries such as the United States, South Korea (n=11), Taiwan (n=9), the Netherlands (n=7), and Hong Kong (n=7).

In sum, it seems the geoLocation cloud follows a pattern similar to the one observed for active variables in section 5.2 above: The cloud has a clear center around sociological,

psychometric, and prevalence study types along with an off-shoot towards the biometric study type. The off-shoot consists mainly of Chinese IA articles, which also causes the centre of the cloud to become relatively less dense compared to the pattern we observed for active variables in bi-plot 2.

5.4 The Development of Internet Addiction (IA) Research Over Time

In this section, I will present a more detailed account of the development of the field of *Internet Addiction* (IA) research over time. In order to better observe their variation, I have zoomed (x30) in on the area that covers their positions using the interactive tool included with the online section of this thesis (see <http://einarstenson.se/MA/#/TMCA>).

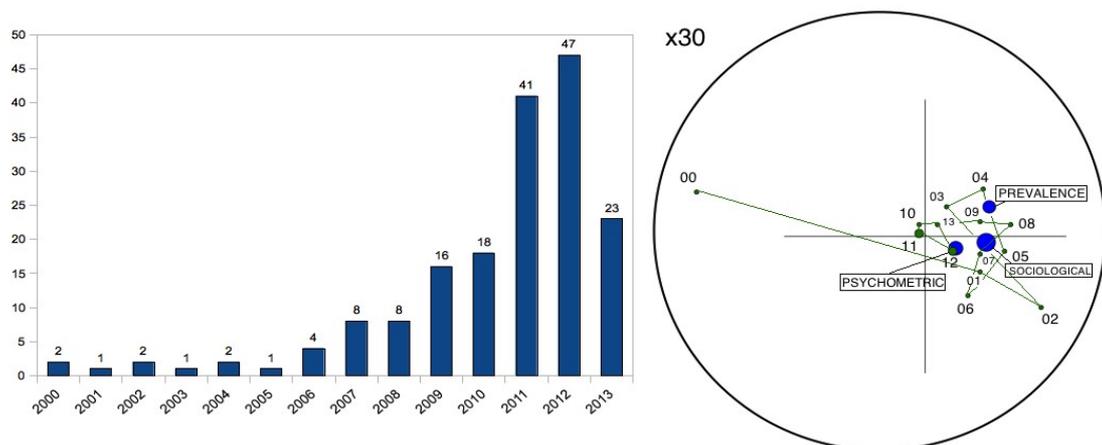


Diagram 5. & Bi-Plot 4. Development of Internet Addiction (IA) Research Over Time. Magnification: 1.05*30. Inertias: P1: 16.6%; P2: 10.8%. n = 174. X: P1; Y: P2.

In diagram 5 and bi-plot 4 above, we can see that, with respect to the theoretical approaches and method variables used in this study, the development of IA research has stabilized over time. Indeed, in its earliest years (2000-2008), we can observe how studies are few in number (from n2000=2 to n2008=8) and vary in their design from year to year, therefore making great leaps across the plot (early-year sub-cloud non-weighted variation = 0.29). Towards more recent years, however, we can see that the number of IA studies grows rapidly (from n2009=16 to n2012=47) and converge towards the center of the field (late-year sub-cloud non-weighted variation = 0.02). In other words, the field of IA research has experienced a rapid growth in the number of articles which, in turn, are increasingly similar.

In sum, the results above display a rapid growth in the number of IA articles over time, which has been accompanied by a stabilization of IA research study designs. We should, however, remain cautious in making these conclusions both because the articles are so few in number and because a number of early year articles were excluded in phase three of the data collection process (see section 4.1.1 above).

6. Discussion

In section 2 above, I stipulated two research questions: (1) to identify the constellations of theoretical approaches, methods, geography, and time in the field of *Internet Addiction* (IA) research and (2) to analyze these from a *Sociology of Scientific Knowledge* (SSK) perspective, which I related to Bloor's (1976) four point conditions for the Strong Programme. Consequently, rather than focus on the philosophical ontology of the IA concept, my aim was to investigate the practices of the community of scientists conducting IA research. Therefore, in the theoretical sections above (section 3), I reviewed Kuhn's (1962) and Frickel & Gross's (2005) conceptualizations of scientific progression as fluctuations between the states of steady, homogenous, and cumulative practices in Normal science, and the rapid and creative flux of Extraordinary science, which is driven forth by *Scientific Intellectual Movements* (SIMs).

To begin with, this study constitutes a study of method practices using *Multiple Correspondence Analysis* (MCA) to the field of SSK research. By mapping the (dis)similarity of articles in IA research in the bi-plots above, I have produced an analytical procedure that can identify the Normal and/or Extraordinary character of a field as it has been theorized by Kuhn (1962) (see section 3.2 above). Indeed, although I have focused my efforts on an exploration of the theoretical change and new research technology and methods dimensions of *Scientific Intellectual Movements* (SIMs) as they were conceptualized by Frickel & Gross (2005) (see section 3.3 above), this procedure could be applied to other characteristics of a scientific field.

In the case of the field under investigation in this study: IA research, I took the development of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM) as my starting point because it played a crucial role in the paradigm shift from a focus on

causal explanations towards the diagnosing and treatment of mental disorders during the 1970s (American Psychiatric Association; Strand, 2011; Mayes & Horwitz, 2005). In particular, I directed my focus on the historical use of methods and their associated theoretical approaches along with their geographical dispersion and chronology as indicators of the homo/heterogeneity of the field of IA studies.

To begin with, I found that IA research has a clear center around sociological, psychometric and prevalence studies, along with a much less frequent off-shoot revolving around biometric studies, which frequently consist of *Magnetic Resonance Imaging* (MRI) studies originating in China (see sections 5.1 & 5.3). In addition, the typical IA study will make use of sociological and/or psychometric diagnostic test instruments in order to investigate populations comprised of either college and/or grade/high school students. These IA studies tend to be confirmatory rather than explorative, where the measurement instruments in question are used as dependent, rather than independent, in their analyses (see section 5.2 above). Thus, the existence of IA is taken for granted, meaning that the goal for most IA researchers seems to be to diagnose the prevalence of and correlate IA with various risk factors rather than outline its ontology. Finally, we can see that the recent annual changes (2009 until 2013) changes in the field's method and theoretical composition are relatively small (see section 5.4), which indicates that it is theoretically and method stable.

My conclusion, therefore, is that the contemporary field of IA research is congruent with the state of Normal, rather than Extraordinary, science. On the other hand, however, we should also note that my analysis of the IA field's early development (2000-2008) indicate rapid annual changes (see section 5.4). There is thus some evidence in support of the proposition that IA studies went through a phase of Extraordinary research in the immediate aftermath of Young's (1997) initial case studies on the subject. This is unsurprising, perhaps, considering the rapid development of *Information Technologies* (IT) and, in particular, *Social Networking Sites* (SNSs) during the 00s.

Nonetheless, as I briefly mentioned in the introduction to this thesis, the IA concept is still highly controversial, both within academia and in the popular debate. Rather than falling back on an assumed bifurcation between the world of science and that of social science and/or popular debate, it is also possible that the field is in fact so polarized that

scientists in different paradigms do not even carry mutual scientific conversations with each other, or indeed use the same terms.

For example, in addition to the IA concept, there are those who distance themselves from the presumably addictive component of Internet use by using the term *Problematic Internet Use* (PIU)⁹ (see for example Davis, 2000; Bergmark et. al., 2011). Davis (2001) proposes that a study of PIU should distinguish between content-specific dependencies on the Internet, such as porn, gambling, and social networking, and those that pertain to the inherent characteristics of the Internet. In particular, he highlights the social aspects of the Internet as a possible source of Internet-specific dependency (Davis, 2001: 188). Similarly, in their study of IA in the Swedish population, Bergmark et. al. (2011) investigate the relationship between specific uses of the Internet and high scores on diagnostic IA variables. They found that once specific uses of the Internet, such as social media, gaming, and Internet gambling were taken into account, the relationship between the amount of Internet use and the IA variables demonstrated a two sided character: In part, higher degrees of Internet use was associated with a higher degree of social and family contacts and, in part, Internet use was also associated with fewer *Face-to-Face* (FtF) contacts (Bergmark et. al., 2011: 4498). In other words, Internet use increased the sociality of its users in general, but decreased their non-Internet social interaction.

In conclusion, although the results of my study lead me to conclude that contemporary IA studies are indeed best characterized as Normal science, I believe the widespread debates and controversies surrounding the IA concept could be an indication that the field is in fact so polarized that the proponents of its Paradigms do not use the same terms or relate to each other's work. Future studies on the development of IA could investigate this further by expanding this study into PIU studies and similar concepts that do not accept the addiction-component in the IA concept. Indeed, it would be interesting to observe what the method differences between them are and how these relate to their theoretical approaches to the seemingly pathological use of the Internet. Finally, and perhaps most importantly, it is important for those who influence the eventual decision to include IA in the DSM to consider the possible ramifications of including a mental illness that is so highly controversial, even if one of its sub-paradigms, IA studies, have displayed a stable development.

⁹Note that although the search term "Problematic Internet Use" was used in the article data collection, studies that did not concern *Internet Addiction* (IA) per se were excluded.

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