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Internet Self-Regulation in Higher Education: A Metacognitive approach to Internet Addiction

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Abstract. Etiological models of Internet Addiction (IA) have repeatedly highlighted the self-regulatory functions of an individual as an important factor in the development and maintenance of pathological use of the Internet. Moreover, neuroimaging studies have shown significant changes in the activity and structure of the prefrontal cortex in Internet Addicts. This brain region is responsible for executive functions such as impulsivity, self-regulation, self control and goal-based decision making. University students have been recognised throughout IA research as an at-risk population. Additionally, IA has recently been strongly linked to risky cybersecurity behaviour, framing students as vulnerable to cybersecurity risks. This paper presents the results of a content analysis which attempted to identify whether technological interventions have been documented within a higher educational context to assist in the prevention of IA through the promotion of self-regulatory functions of Internet use. No studies were found which met the primary objective of the analysis however, secondary objectives were achieved. Various novel findings, as well as some consistent with previous research in the field, were derived from studies that could be used towards a preventative intervention which leverages metacognitive components.

Keywords: Internet Addiction · Risky Cybersecurity Behaviour · Prevention · Self-Regulation · Meta Cognition

1 Introduction

The Internet has undoubtedly had a profound impact on individuals. However, the social, psychological, educational and vocational impact of excessive use of the Internet, given its evolving nature, is difficult to track. Research into overuse of the Internet to the point of pathological behaviour and markers of addiction provides mounting evidence that frequent use of the Internet opens individuals to the possibility of Internet Addiction [27, 48, 44]. Moreover, undergraduate student populations appear especially vulnerable [3]. Additionally, IA has recently been explicitly linked to risky cybersecurity behaviour [24], which could leave university students at higher risk for cybersecurity threats.

Various perspectives and aetiological models have been theorised and expanded on in an attempt to isolate the cognitive mechanisms which are involved in the development and maintenance of Internet Addiction. Understanding these mechanisms allows for more informed interventions to be put in place to prevent and treat this problem. One such mechanism is self-regulation [15]. Previous research by the current authors suggest that universities likely house repositories of network data, objectively revealing the student populations' Internet behaviour on campus. This could be leveraged to gather insight into students' Web usage behaviour or provide students with information about their own Web behaviour for reflection and self-regulation [57].

The present study sought to ascertain whether research has been done in line with this use of data for self-regulation or which provides insights that could inform a preventative intervention grounded in metacognition within a higher education context. Metacognition refers to 'thinking about thinking'. It involves monitoring ones thoughts towards goal through executive control or self-regulation [17].

2 Internet Addiction, Higher Education and CyberSecurity

The conceptualisation of IA surfaced as the result of a light hearted look at pathologising common behaviours. Psychiatrist Dr. Ivan K. Goldberg posted this notion on a forum he created to remark on the rigidity of the Diagnostic and Statistical Manual of Mental Disorders (DSM-4) substance dependence criteria. However, this satirical proposal revealed a real possibility which mobilised academic inquiry [28]. The pioneer studies were conducted by psychologists Dr Mark Griffiths and Dr Kimberly Young [27, 48]. However, some reviews attribute the first conceptualization and empirical research on Internet overuse to Dr Young [59, 13].

There are multiple perspectives on IA and accordingly is referred to by various terms such as 'Problematic Internet Use', 'Pathological Internet Use', 'Internet Addiction' and 'Internet Dependence' [44]. Although IA has been controversially used and labelled as a misnomer as the term addiction itself is not officially recognized, it is still the most widely adopted, used as an umbrella term for describing various pathological behaviour associated with Internet use [44]. For this, reason and for linguistic brevity, the term IA will be used in this study, with the exception of studies requiring a specific model derived term for IA. Research in the field has resulted in multiple models focusing on various aspects of IA at differing granularities. For example, some depict the high level overall development [15, 51], specific types of IA [41, 12] and low level specific causal factors and/or relationships [9, 10, 11, 30, 31].

Despite the lack of consensus in the field regarding the conceptualization, clinical relevance and significance of IA, there is abundant evidence that excessive use of the Internet can lead to scenarios where individuals can experience severe negative psychological, physical, vocational and social outcomes in the same ways as substance abuse [33, 62]. One of the major models of IA, the components model has continuously asserted that addictions not involving a substance or chemical i.e. behavioural addictions, should be treated and recognized with the same authority as substance abuse. The model shows how IA can lead to negative underlying psychological and life scenarios which parallel substance addictions [22, 23].

The first formal high level model which contributed to addressing the question of what Internet users are getting addicted to, is the Cognitive-Behavioural Model of Pathological Internet Use (CBM-PIU) developed by Davis [15]. The model makes an important distinction between Generalized Pathological Internet Use (GPIU) and Specific Problematic Internet Use (SPIU). GPIU typically accounts for information searching and communication features of the Internet. Whereas, SPIU refer to specific online activities which have distinct characteristics. The most prevalent are namely, Cybersex, Online Gambling and Internet Gaming. However, certain psychological factors would be common across all forms of IA, shown by models which depict the factors shared across all instances of addictive behaviour [51]. The DSM-5 has recently acknowledged gambling as a behavioural disorder and has included Internet Gaming Disorder as a possible formal disorder warranting further research for inclusion [2].

The reality and severity of IA is evident in the IA research field and it has been repeatedly asserted that undergraduate university students are a high risk population for IA. University populations have been considered to be at-risk in early stages of IA research [45, 29] and this is found to be the case throughout the expansion of IA research and in contemporary studies [34, 53, 3]. Numerous reasons for this have been suggested. For example, students have a tendency towards Internet use given its abundant utility, likely have unlimited free access while at university, flexible schedules and a sparsity of parental coercion. Additionally, young adults entering university are typically experiencing a time which requires the development of an identity, new relationships and self reliance [59, 34]. University students are vulnerable to loneliness and/or depression, which are well recognized precursors and co-morbidities of IA [31, 11, 60]. Moreover, the 18-25 age period has been noted as being an especially opportune period for the emergence of addiction forming behaviours [22].

In addition to this, IA has been found to be associated with cybersecurity risk factors. Hadlington [24], explored how cybersecurity attitudes, impulsivity and IA relate to risky cybersecurity behaviour. This recent study found that IA and impulsivity are a significant predictor of risky cybersecurity behaviour. The author notes that, to date, there “have been no explicit attempts to link IA to risky cybersecurity behaviours” [24]. Hadlington’s study has since been replicated, presenting the same findings, adding to the robustness of the relationship [1]. To the present authors’ knowledge, the mediating effect of impulsivity between IA and risky cybersecurity has not yet been studied. The full possible causal pathways between these three factors have yet to be established. It is worth noting that IA has previously been found to be associated with impulsivity and has been proposed as an impulse control disorder [7, 54]. Therefore, risky cybersecurity behaviour may result from impulsivity which was originally fostered by IA. Research into the cognitive factors involved in the development and maintenance of IA has shown that deficient self-regulation is a major

contributing factor. Various reviews on neuroimaging studies have shown that individuals with IA have structural and functional changes in their pre-frontal cortex, the area of the brain responsible for executive functioning. This effects the efficiency of self-regulatory cognitions such as decision making towards goals, compulsivity and self control [33, 8, 52]. IA is a clear candidate for compromising an individuals cybersecurity safety. Another possible way that IA could harbour increased cybersecurity risks is that IA has been linked to the use of online piracy [46] which is prone to a host of cybersecurity risks [26].

A recent and pioneer literature review on the prevention of Internet Addiction [58] explicitly asserts that there is a scarcity of literature on the prevention of IA, and research towards preventative interventions for at-risk populations should be undertaken. Moreover, a review of media multitasking and cognitive interventions [47], noted a lack of clarity in intervention studies with regards to effects on behaviour.

The present study forms part of a larger research study which is developing a framework to allow higher education institutions to use data generated from on-campus Web usage to assist students in preventing IA by providing them with useful objective views of their Web usage. The study, therefore, sought to systematically explore the literature to determine if self-regulatory focused technological interventions or preventative approaches had been formalized within a higher education institution to combat IA. The technological aspect of the larger research study is based on the assertion that self-reported use of media is typically unreliable and a more objective view would be more accurate and relevant [20, 55]. For example, the use of network traffic logs or usage monitoring software. Moreover, it is premised on the self-regulatory factors described in Social Cognitive Theory [4, 5] as applied in IA research [36, 38, 39, 37] and the fundamental hypothesis established in personal informatics that monitoring ones data allows for insights on behaviour which lead to behaviour change [16].

Abstracting and leveraging Web usage data within a higher education setting can be done in countless ways. Understanding how to do this in an intervention alongside other intervention success factors, in a way that fosters engagement and desirable outcomes is important, as engagement and efficacy of productivity personal informatics software has been noted as problematic. There is then a need to consolidate research to allow for interventions to be designed for success, especially considering the importance of higher educational success, for which higher education institutions are responsible for fostering.

3 Method

The primary objective of this content analysis was to establish the existence of studies on technological facilities which are designed to support students self-regulation of their Internet behaviour. The secondary objective was to establish findings of studies considering how Internet use and self-regulatory functioning within university students can be supported and understood to inform an intervention or prevention program.

A search was conducted on seven academic databases. Namely, ACM, ERIC, Scopus, IEEE, Goggle Scholar, Science Direct and Web of Science. These databases cover disciplines of education (ERIC), information and communication technology (ACM and IEEE) and cross disciplines (Google Scholar, Scopus, Web of Science). Table 1 shows the keywords and terms used in the search.

The search formula was oriented as:

Table 1. Keywords

Web use	["Web Usage" OR "Internet Usage" OR "Web use" OR "internet use" OR "Web behavior" OR "internet behavior" OR "Web self efficacy" OR "internet self efficacy" OR "Web self-efficacy" OR "internet self-efficacy" OR "Computer Usage" OR " Computer use" OR "Computer behavior" OR " Computer self efficacy" OR "Computer self-efficacy" OR "Web behaviour" OR "internet behaviour" OR "computer behaviour"]
Metacognitive	["self-monitor" OR "self monitor" OR "behaviour change" OR "behavior change" OR "personal informatics" OR "productivity" OR "feedback" OR "self regulation" OR "self-regulation" OR "quantified self" OR "quantified-self" OR "self-monitoring" OR "self monitoring" OR "self regulate" OR "self-regulate" OR "reflect" OR "reflection"]
Technology	["technology" OR "intervention" OR "application" OR "widget"]
Education	["education" OR "university" OR "college" OR "undergraduate" OR "student" OR "tertiary"]

[Web use keyword] AND [Feedback keyword] AND [Technology keyword] AND [Education Keyword]

The initial number of results produced for each database are as follows (total n = 2258). ACM Digital Library (339), ERIC (87), IEEE (56), Google Scholar (312), Scopus (619), Web of Science (19), Science Direct (826).

A total of 2234 results were screened after duplicates were removed (n = 24). Titles and/or abstracts were screened manually for articles which may have attempted to avoid or understand Web usage behaviour that has a negative effect on a university student population. Additionally, any indication that metacognitive functioning of students was being investigated or proposed as an intervention was included. Table 2 depicts the filter criteria used. Articles which appeared to meet these criteria were collected for analysis (n = 52).

Table 2. Filter Criteria

1:	Paper must be peer reviewed
2:	Attempting to avoid or understand Web usage behaviour that has negative effects on the population
3:	Emphasis on self-regulation or metacognitive factors of behaviour
4:	Undertaken in or focus on a Higher educational environment

These full text articles were manually screened for study method, population, context, objectives and results. Articles which did not meet the criteria were removed, leaving a final sample for analysis (n = 9). The final sample shown in Table 3 represents studies which either attempt to understand the relationships between self-regulation and Internet use within a

higher education setting and/or suggest ways in which universities could approach reducing the negative impact of excessive Internet use in a student population. The study designs were compared and the findings were classified as either confirmatory or informative. The studies which were confirmatory contain findings which contribute to previously established trends in the field. The studies which were classified as informative contributed directly to the secondary objective of this study.

It must be noted that the primary objective of a deductive analysis could not be realized. No studies were found which used or tested a technological intervention facilitating or promoting self-regulation of university students' Internet usage. Therefore, the studies included in the final sample contribute only to the secondary objective. An inductive approach was used for the secondary objective to extract and consolidate findings which may inform such an intervention.

4 Results and Discussion

All but one study in the final sample, shown in Table 3, used a university student population to gather data for the study. The majority of the studies ($n = 8$) employed a survey approach.

Seven studies reported findings which were consistent with previous research. Most of these consistencies are explicitly mentioned within the study. Moreover, additional consistencies were found by the present authors. However, using informative findings was the focus of this paper and therefore, the confirmatory findings will not be detailed.

Four studies reported findings which could be used to inform an intervention [61, 18, 19, 35]. Each of these studies are individually reviewed then discussed in terms of its applicability to the larger research study from which this study stems.

The intended manifestation of the larger study's framework is a preventative technological intervention which is scalable and calibrated based on relevant research findings. As such, although there are notable ties to other research in the field of IA and personal informatics and the reviewed studies findings, the secondary objective relates to informing this emerging framework. Therefore, in depth discussions of these ties are not prioritized. The focus is the aggregation of findings which can inform the intervention design aspect of the framework. This may be of value to other studies attempting to develop preventative measures for IA and in turn reduce risky cybersecurity behaviour.

Wu's study [61], the first of the four studies, investigated the degree that students are aware of their focussed attention during online learning sessions. Moreover, which self-regulatory strategies do they use, if any, and whether distinct meta-attention profiles can be derived from these. The study is based on the premise that university students typically learn and engage in academic tasks within an online environment. Moreover, the likelihood that students will engage more actively with social media during formal and informal learning is evident in the development of pedagogical models which advocate actively using social media applications such as facebook, youtube and flickr to support and facilitate learning [14]. The result is often a learning environment in which students constantly need to control the urges to engage with other online activities available to them when undertaking online learning tasks.

These Personal Learning Environments (PLE) have many information stimuli in the form of social media notifications and the availability of task switching to any other website or search engine amongst others. Each of these stimuli require exertion of self control to

Table 3. Final Sample

Study	Size	Type	Cross Sectional Longitudinal Review Testing Correllational Factors of Internet Use Discovering Self-Regulatory Factors Proposing Literature Derived Recommendations Confirmatory Informative Regression Analysis Structural Equation Modelling Descriptive Statistics Cluster Analysis											
			Method			Focus			Findings		Evaluation			
[50]	814	1st Year	x			x			x		x			
[49]	508	1st-4th Year		x		x			x			x		
[61]	230	1st-4th Year		x			x		x	x			x	x
[56]	380	1st-4th Year	x			x			x			x		
[18]	97	1st-4th Year	x				x			x			x	
[19]	512	1st-3rd Year	x				x			x			x	
[21]	-	-			x			x	x					
[55]	631	1st-4th Year	x			x			x		x		x	
[35]	348	1st-2nd Year	x				x		x	x			x	

maintain attention on the task at hand which may lead to reduced self control of subsequent tasks, as self control has been depicted as a finite resource [6].

The study is grounded in theories of attention, meta-attention and meta-cognition. Attention is defined as the selection of information stimuli for further processing, meta-attention then being an individuals awareness of selection of information stimuli for further processing. Meta-cognition is the reflection on ones thoughts and is central to the learning process. However, the authors argue that meta attention is a crucial part of online learning in that it initiates and maintains focus for online learning tasks, which then allows meta cognitive processes to partake in learning. Meta-attention is a less widely studied field. The authors juxtapose meta-attention and meta-cognition to operationalize meta-attention based on established work on meta-cognition. From this comparison a framework for meta-attention was derived.

The framework defines two main components. Knowledge of Attention (KA) and Regulation of Attention (RA). Applied to PLE for the study, KA refers to the acknowledgement or awareness of sustained attention or lapses of attention. RA refers to the regulatory strate-

gies used by students to maintain focus. This framework was used to profile students based on measures of KA operationalized as Perceived Attention Discontinuity (PAD) and Social Media Notification (SMN). PAD refers to awareness of attention and engagement shifts or disruptions. SMN refers to the degree that a student is anticipating or considering social media notifications during a task.

RA, was operationalized as Behavioural Strategies (BS) and Mental Strategies (MS). BS refers to behavioural techniques employed to reduce distraction during online learning tasks, MS referring to cognitive techniques to reduce distraction.

The measurement instrument of this framework was developed through semi structured interviews and labelled the Online Learning Motivated Attention and Regulatory Strategies scale (OL-MARS) which comprised twenty 5 point likert scale statements to which a participant indicated to what extent they agree or disagree. For example an item to measure PAD was “I often turn on the computer for studying (e.g., writing paper, learning, or searching information), but find myself always doing irrelevant things (e.g., watching YouTube, using Facebook, reading online news, or playing games)” or for SMN “I constantly watch out for the sound or pictorial signals from smartphones, Line, Facebook, or other devices and applications”. An example of a BS item was “I use strategies to help myself focus on my work (e.g. unplugging, closing unrelated windows, or limiting the speed of upload/download) when using computers.” and for MS “If I can focus on what I should do when using the computer (e.g. write paper, learn or search information), I will feel happy and feel a sense of achievement”.

The OL-MARS was distributed to 230 university students (predominantly undergraduates) with additional measurements of cluster validation variables such as Internet Self-Efficacy, Internet use, academic achievement and online information searching strategies, which were used to test the validity of clustering of the students based on KA and RA measures as well as provide further insight into the meta-attention profiles’ online learning characteristics.

Results of a K means clustering analysis revealed 5 profiles reflecting different levels of KA and RA. The measurements for each of these profiles for KA (PAD and SMN) and RA (BS and MS) is shown in Figure 1 and further described below:

- **Motivated Strategic (MST)**
 - a low level of PAD and low level of SMN accumulatively a low level of KA.
 - a high level of BS and MS, accumulatively the highest RA score.
- **Self Disciplined (SD)**
 - a very low level of PAD and SMN accumulatively a very low level of KA.
 - a medium level of behavioural and mental strategy accumulatively a medium RA score
- **Hanging On (HO)**
 - a high level of PAD and a medium-high level of SMN accumulatively a medium-high level of KA.
 - a medium level of behavioural and mental strategy accumulatively a medium RA score
- **Non Responsive (NR)**
 - a high level of PAD and very high levels of SMN, accumulatively a high level of KA.
 - a very low level of behavioural and a low level mental strategy, accumulatively a low RA score

– **Unaware (UA)**

- a medium-low level of PAD and SMN accumulatively a low level of KA.
- a low level of behavioural and mental strategy accumulatively a low RA score

It is worth noting that PAD is described in the study as “perceived attention and engagement problems”. This means that a low score in this may represent an absence of engagement problems or the absence of awareness of attention and engagement problems. In other words, a high score of PAD means an individual is aware of and therefore implies a presence of attention problems. However, lack of awareness of an attention problem may indicate in some profiles that there is little or no attention problem or there is an attention problem but no awareness thereof. This is not clarified in the study, however it may be safe to assume that within the groups which have low PAD measures that other variables may determine which of these instances are being observed.

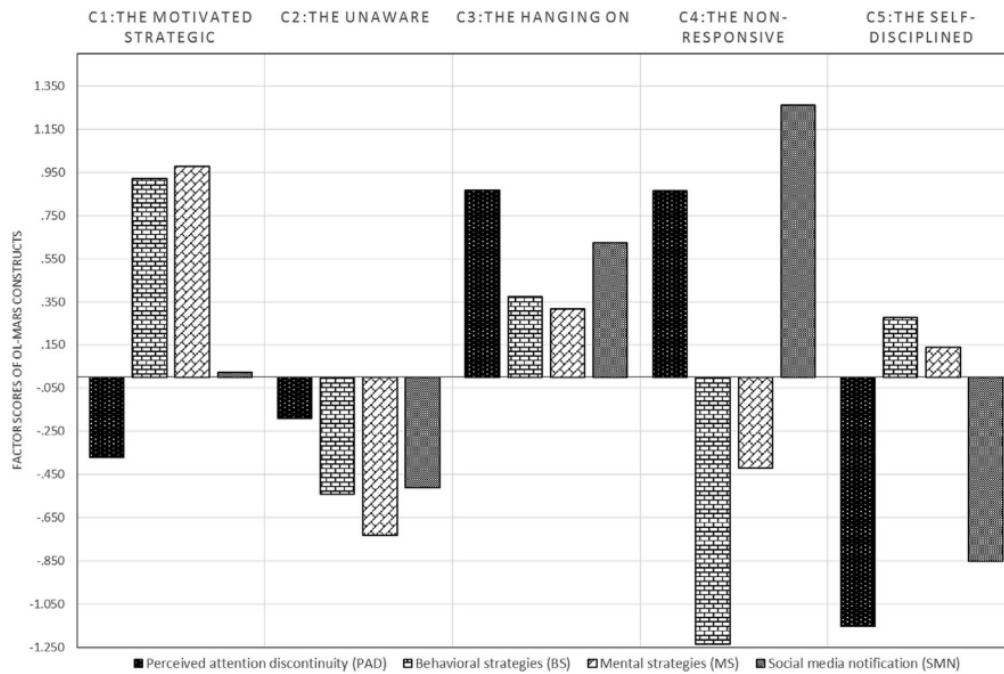


Fig. 1. OL-MARS Profiles [61]

The cluster validation variable values for each of these profiles can be seen in Figure 2. Of particular interest is final grade. Given the success criteria for a PLE outcome is academic success for that course. Some insight can be gathered from considering the profiles in accordance to their final grades represented as z_{final} in Figure 2.

The MST had the highest final grades, followed by the SD, HO, UA and NR. RA seems to have the most impact in terms of final grades as KA scores were low for MST and SD who were both at the top of the final grade standings. The two profiles lowest in final grade

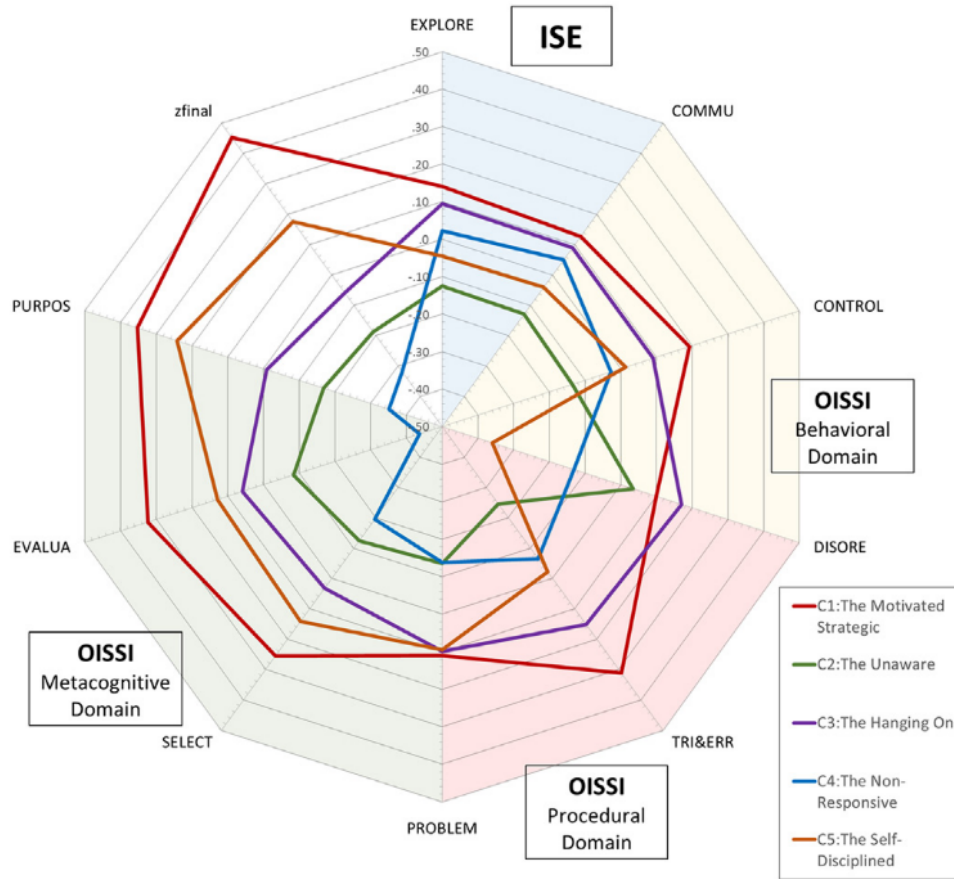


Fig. 2. OL-MARS Profiles Validation Variable Relative Values [61]

scores both had low RA whereas the other profiles all had medium to high RA. The absence of RA seems to be highly impactful whereas KA does not strongly correlate. In short, the use of RA was positively associated with academic achievement.

This further indicates meaning for PAD scores. The SD scored lowest in PAD and second highest in final grades, indicating that the PAD may reflect a high percentage of that score is due to lack of awareness and not necessarily actual attention problems. Alternatively, the MS and BS may be reducing attention problems directly and therefore, there are none to observe.

Some correlations between meta-attention and cluster validation variables were considered. However, the variances in Internet use variables amongst the profiles did not implicate clear statistically significant correlations to academic success, although the profiles did have clear differences in Internet use patterns. The authors state that

“These findings suggest that regulation and knowledge of attention play a role in online learning beyond ISE and search strategies and have a unique standing in online learning.”

Overall, the results indicate that the proposed meta-attention framework is valid and can be used to measure students KA and RA. The study findings point out that awareness of attention is not in itself enough to maintain control in online learning, RA is a key component to success.

Implications for an institutional intervention are that certain OL-MARS profiles require specific training for improvement. OL-MARS can be used to identify an individual’s KA and RA to calibrate an intervention for greater effect. Specifically, increasing RA in profiles who lack MS and BS may make an intervention more effective at increasing self-regulation of Internet use.

The principle hypothesis proposed by personal informatics (gathering personal behavioural data for reflection through technology) is that insights gathered from objective views of behaviour lead to behaviour change. However, a review of PI systems [16] revealed that many studies testing PI systems indicated that the participants acknowledged correct objective views of their behaviours but did not know how or were not motivated to change their behaviour. The disconnect between importance of RA versus KA found in Wu’s study reflects this. However, certain MS or BS may require or benefit from objective views of Web usage behaviour. An intervention would need to provide an indication of this lack of RA and provide MS or BS suggestions or tasks for training RA. This is discussed further in the future research section.

The following two studies [18, 19] together comprise a total of four studies which extend a single line of enquiry. As such they will be reviewed together as they have accumulative and cohesive findings.

Dunbar, Proeve and Robert’s study [18], the second of the four studies, was based on the dual representation model of goal directed behaviour by Ayelet Fishbach and colleagues. It tested whether the presentation format of a possible action effected how an individual valued subsequent behaviours as either congruent or incongruent towards a goal. This represents insight into how an individual’s self-regulatory system can be put in a state which will in turn effect the likelihood of certain actions. This approach had been used in marketing and consumer scenarios but not in clinical settings considering IA. Participants were primed to set their unconscious behavioural goals to ‘reduce their Internet use to avoid IA’. They were then presented with two behavioural actions. One was congruent with avoiding IA, for example do some academic work, socialize in person with some friends. The other was not, for example do some online shopping, browse reddit. These two actions were then presented as either conflicting or harmonious. For example, you complete an online assignment **OR** browse reddit. You complete an online assignment **AND THEN** browse reddit. The first example forms a commitment self-regulatory framework, whereas the second forms a progress self-regulatory framework. Individuals in a commitment framework view subsequent congruent actions more highly than when in a progress framework. The reverse is true for individuals in a progress framework who value incongruent behaviours more highly. The differences are shown in Table 4.

Dunbar, Proeve and Robert’s study [19], the third of the four studies, extended their previous study [18]. Given the studies initial findings, further aspects of Fishbach’s model were explored in the same context. It comprised three studies.

Table 4. Dynamics of self-regulation model [18]

Representation	Commitment	Progress
Promotes	Highlighting of the focal goal	Balancing between all goals
Leads To	Emphasizing the focal goal at the cost of alternate goals (temptations)	Valuing alternate goals (temptations) as well as focal goal
Causing	Focal goal behaviors increase in perceived value. Alternate goal behaviors (temptations) consequently decrease in perceived value	Alternate goal behaviors (temptations) increase in perceived value. Focal goal behaviors consequently decrease in perceived value

Study 1 confirms that commitment and progress frameworks can be primed. Furthermore, it can be achieved through the use of basic questions. The study found that subsequent feedback about actions towards a goal elicit different value systems depending on the type of feedback, positive or negative and which framework an individual has adopted. Positive feedback prompts a different set of perceived values of congruent behaviour in a commitment framework versus a progress framework. Individuals adopting a commitment framework who are given positive feedback about goal attainment, perceive congruent behaviours with greater value and incongruent behaviours with lower value. However, when given negative feedback about goal attainment, individuals perceive incongruent behaviours with greater value and congruent behaviours with lower value. The opposite was found to be true for the progress framework. Negative feedback highlighted the gap in progress and in turn increases their perceived value of congruent behaviour. Positive feedback reinforces their progress and therefore adds to a higher perceived value of incongruent behaviour. Figure 3 shows behaviour goals applied to Internet use and academic work, a common scenario in higher education. The summarized responses to feedback are shown in Table 5.

Study 2 tested how the presentation format of feedback about behaviour towards a goal effects perceived behaviour values in individuals adopting a commitment or progress framework. The frameworks were primed in this study by promoting engagement to the overall goal of reducing personal Internet use. High engagement and commitment was achieved by exposing some individuals to additional literature on PIU which prompted a progress framework, the remaining individuals were considered to have low/uncertain engagement or commitment, which elicited a commitment framework. Feedback was presented by highlighting what has been accomplished rather than what still needs to be accomplished. I.e. to-do versus already done. Individuals exposed to feedback highlighting achievement (already done) perceived it as positive whereas feedback highlighting the need for further achievement (to-do) was perceived as negative.

Consistent with study 1, individuals adopting a commitment framework viewing positive feedback, perpetuated their higher value placement in behaviours which are in line with their goal. This type of feedback framing caused individuals adopting a progress framework to reduce their perceived value of behaviours which are congruent with their goal. The opposite was true for feedback highlighting pending progress or progress deficits. Individuals in the commitment framework lowered the perceived value of their congruent goal behaviour and progress framework individuals perpetuated value their congruent goal behaviour. This

showed **how** positive and negative feedback is perceived differently depending on the framework adopted at the time of seeing the feedback.

Progress framed individuals are more interested in progress as they have no doubts about their commitment. When viewing confirmation of progress (already done), they feel accomplished and satisfied and subsequently consider other activities. Whereas, commitment framed individuals are unsure of their commitment levels and re-evaluate and bolster their commitment to the goal because the progress indication gives them reassurance that the goal is possible, as such they continue to focus on goal related activities and do not consider others with more value. Progress framed individuals note incomplete progress as a problem and work to correct the discrepancy in progress whereas commitment framed individuals are more convinced that the goal is unattainable and their commitment wavers, goal congruent activities then have less value.

Study 3 considered whether individuals who perceived their goals as abstract/high level or as distinct/concrete actions prompt a commitment or progress framework and therefore experience alterations to their perceived value depending on the feedback provided. It was confirmed that individuals who perceived their goal as abstract triggered a commitment framework which altered the feedback effect of behaviour values as per the previous studies. Conversely, concrete goals triggered a progress framework and the associated feedback alteration effects. These studies strongly support the use of self-regulation and the ability to tailor feedback effects by priming commitment and progress frameworks in individuals. Moreover, this model holds true in and is rooted within the context of IA within a university environment.

Table 5. Feedback Frame Response Summary [19]

Factors that promote congruent behaviour (Goal Directed)	Factors that promote incongruent behaviour (Temptations)
Progress frame with negative feedback <ul style="list-style-type: none"> – A discrepancy is observed between actual and desired goal attainment – Congruent goal behaviour is more attractive 	Progress frame with positive feedback <ul style="list-style-type: none"> – Balancing occurs – Enough has been done pursuing the goal for now, other behaviours seen as more attractive
Commitment frame with positive feedback <ul style="list-style-type: none"> – Highlighting occurs – Congruent goal behaviour is more attractive 	Commitment frame with negative feedback <ul style="list-style-type: none"> – Commitment to goal is questioned, the goal is seen as less important – Other behaviours are now more attractive

Overall the studies by Dunbar, Proeve and Robert [18, 19] show that the order and format of information presented is important as it primes internal self-regulatory systems which effect perception of feedback as well as the value of subsequent behavioural choices. Moreover, the presentation of data itself effects the activation or deactivation of these systems.

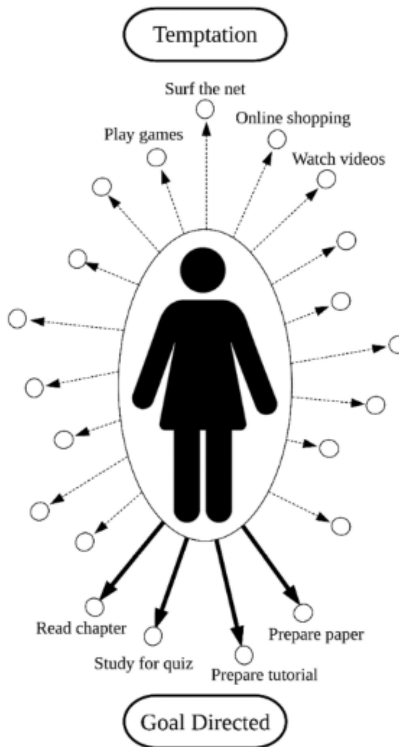


Fig. 3. Academic and Internet Behaviour Conflict [19]

This demonstrates the importance of intervention interaction feature design for effecting behaviour regulation.

In terms of how these findings can be leveraged in an intervention specifically, the initial study by Dunbar et al [18] as well as study 1, 2 and 3 from [19] indicate that self-regulatory frameworks can be primed by presenting possible actions as complimentary or conflicting, through the use of basic questions, by the setting of abstract vs concrete goals as well as increasing engagement levels. As such, the implications for the proposed intervention are that activity options or suggestions, questions, goal setting or engagement promoting features should be used to prompt appropriate framework. There are numerous ways this could be done depending on the intervention platform.

Of these three approaches, goal setting is the most applicable for digital interventions. Setting goals and being reminded of them are not uncommon amongst productivity management and personal informatics systems, and these designs could be calibrated to allow for abstract or concrete goal setting depending on subsequent feedback options. Moreover, goal setting has overlapping benefit with self-regulation, as goal setting has been noted as an important aspect of self-regulation [42] and is well understood. Therefore, it can be beneficial in more ways than only prompting self-regulatory frames. It is then more likely to be included in an intervention regardless of framing potential. Goal progress has also

been noted as a promising feature in personal informatics studies which result in actionable behaviour change [16]. Therefore, the same benefit could be gained from re-factoring an already desirable feature instead of including features which may be cumbersome in an already possibly invasive intervention. Alternatively, engagement or commitment levels could be predetermined, which may remove the need to illicit a self-regulatory framework for certain individuals. However, if commitment levels are low it may be too taxing for an intervention to impart high commitment or engagement, in which case the goal priming approach may be more suitable. These goal priming effects were easily done in the study and can therefore be recreated within an intervention.

Study 1 and 2 from [19] demonstrated the effects of negative vs positive feedback on subsequent value ratings of behaviours depending on the self-regulatory frame the individual is in when receiving the feedback. Kim et al [32] tested the effects of negative and positive framed feedback on engagement in a productivity management application called TimeAware. They found that framing productive Internet use progress negatively increases engagement with the application, whereas positive productive Internet use progress framing reduced engagement significantly. This was found throughout the user sample. However, the study did not test for framework priming or subsequent behaviour valuing and can therefore not be directly compared. However, the Timeaware study did further indicate that constant negative feedback was stressful and this should be considered for the long term effect of the intervention.

Study 2 found that feedback depicted as to-do was perceived as negative regardless of framework, only the subsequent value systems are effected by self-regulatory framework state. This notion that framing progress as to-do is perceived as negative is consistent with the disengagement as a result of the positive feedback for the entire sample from the TimeAware study and engagement when negative feedback is given. Suggesting that if negative feedback improves engagement, then interventions should illicit a progress framework prior to negative feedback exposure as this will increase the perceived value of congruent behaviour. Promoting the setting of concrete goals may best serve as a precursor to negative feedback as it will illicit a progress framework and would therefore value congruent behaviours more highly.

Dunbar, Proeve and Robert's studies reveal layers of interactive effects from how information is presented and how it actually effects behaviour and should be carefully considered. Importantly the self-regulatory framing and intended overall goals should be considered before presenting feedback on behaviour and performance.

Labăr, Vincețiu and Țepordei [35], the last of the four studies, correlated the various possible combinations or profiles of time perspectives with multitasking during lectures using PIU as a mediating factor. Based on the time perspective assertions by Zimbardo and colleagues that individuals have subjective internal representations of time, categorized as past negative (PN), past positive (PP), present fatalistic (PF), present hedonistic (PH), and future orientation (F). PN depicts a pessimistic and unsavoury attitude towards the past and past events. PP depicts an optimistic, pleasant and auspicious view of the past. PF represents a perspective of the present as hopeless and negatively deterministic. PH represents a perspective of the present as short sighted, risky and self-indulgent. F represents a perspective of the present as long term goal oriented and forward thinking.

A significant positive relationship between PIU and multitasking was found. Individuals with high levels of PIU have high levels of multitasking traits. PN time perspective

was found to be significantly positively correlated with PIU. This suggests that students who have a proclivity to highlight and remember negative events are more prone to PIU. Whereas, F time perspectives negatively correlated to PIU in a significant way. This suggests that a tendency for foresight was associated with less risk of PIU. No significant correlation was found with PIU and PP. Moreover, the intuitive positive relationship between PH and PIU was not found. Similarly, PF and PIU did not hold a correlation despite PF being strongly associated with PN. The relationship between time perspectives and multitasking are mediated to some degree by the level of PIU. PIU entirely mediated the positive relationship between PN and multitasking in class. This suggests that students who hold a pessimistic view of their past and/or have a proclivity to highlight and remember negative events are more prone to multitask, the Internet being a major expression thereof in class and likely outside of class. The expected relationship of PH positivity correlating to PIU was not found. A study looking at sensation seeking as a predictor of PIU made a similar assumption about seemingly impulsive traits and PIU. The same result occurred in that the expected relationship did not appear [40]. The notable findings from Labăr, Vincețiu and Țepordei's study are that a F time perspective, which has previously linked to personality trait conscientiousness, depict a desirable profile for controlling multitasking during class and low risk of PIU. Suggesting that the ability to delay gratification has some bearing on avoiding PIU, likely because of higher levels of self control associated with it. A PN time perspective was found to encompass more active multitasking during class and higher risks of PIU. This time perspective has been previously associated with anxiety, depression and likely loneliness which are recognized predictors of PIU [31, 11, 60]. This reiterates the importance of regulation of attention, as multitasking is often an expression of lack of focus and not parallel processing which has been wrongly associated with interpretations of millennials. Media multitasking online has also been found to be associated risky cybersecurity behaviour [25]. The study concludes that time perspective coaching could be used to elevate PN time perspectives. However, this method requires expertise outside of typical higher education settings.

The implications of these findings for an intervention are that no clear findings can be translated directly into an intervention feature without further research into time perspective coaching. However, this does provide an additional possible avenue of inquiry which may translate well into intervention design, this is discussed further in future research. However, similar to meta-attention trait profiles in Wu's study, students can be prescreened for PN time perspectives and features of the intervention can be calibrated assist in PN time perspective coaching.

5 Limitations

Each of the seven search engines used for the analysis sample selection have unique search filtering interfaces. Therefore, the search formula used in this study needed to be calibrated based on the search engine used. This was done by testing the filtering mechanisms for consistency through spot checks and re-calibration. However, it is possible that some papers were not retrieved correctly by the search engines due to filtering logic flaws. Moreover, the searches were conducted in May 2019 and therefore will not include any published research since then. The search results were manually screened, first by title, then if flagged as possibly relevant was screened by abstract. Then if still found relevant it was read and reviewed for

relevance towards the objective. As the field is still subject to terminological disparity there is of course room for human error. Therefore, the sample cannot be considered flawless. Studies using students' self reporting of Internet use may be further limited as research on IA has shown that self reported data are not completely reliable.

6 Future Research

Informative findings from this study need to be pragmatically applied to a preventative intervention prototype. Further research is needed to determine how these findings can be practically implemented, bearing in mind the availability Web usage data.

For Wu et al's study, establishing valid mental and behavioural strategies in the context of online learning requires further research perhaps derived from behavioural science and/or clinical psychology. Specifically, given that attention regulation has been promoted by Wu and Dunbar, Proeve and Robert and has clear importance for inclusion in interventions, understanding how these will be correctly and appropriately implemented within an engaging and useful platform in an online learning environment is necessary. Although less emphasis was placed on the reflective aspects of attention, certain mental and behavioural strategies may require or benefit from objective views of Web usage behaviour.

Labăr, Vincetiu and Țepordei suggestion of time perspective coaching requires that this technique be analysed for applicability within an intervention. If this coaching technique requires extensive and highly specialized long term sessions it may not be suitable. This remains to be seen. The time perspectives and subsequent behaviour traits found in their study suggest that there may be some correlation to the OL-MARS profiles from Wu's study. These correlations could be tested and merged to further refine possible prescreening functionality of an intervention as previously discussed.

These proposed features and findings can be designed and merged with research on software development design recommendations for productivity monitoring software such as [43].

7 Conclusion

Self-regulation is a fundamental trait which needs to be considered by universities if they intend to support their students in avoiding the negative effects of Internet use. This study consolidated research through useful insights into ways in which metacognition can be positively effected through carefully structured interventions, as the way in which information is presented effects different individuals' cognitions in significant and distinct ways. Moreover, certain student cognitive profiles could characterise certain students with higher risk of IA who would benefit from more specific intervention features.

Cybersecurity behaviour is a multi faceted phenomenon and metacognitive facets should be leveraged to prevent students' and universities' digital assets from being compromised. It is important that universities be more proactive in facilitating the improvement of students' metacognitive functioning and consider the repercussions of IA in order to mitigate risky cybersecurity behaviour.

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