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Effects of internet addiction scores on informational search by undergraduate students☆

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ABSTRACT

The study examined the relationship between internet addiction and university students' use of a network to gain information. Two hundred undergraduate students (aged 18–21 years) were recruited from Science, Social Science, and Arts faculties. They each had 30 min to browse one of two network architectures: a simple hierarchal structure, or a complex relational structure. After the session, they took a test on the content of the network, completed the Internet Addiction Test (IAT), and were asked about their time spent on the internet. There was no effect of university faculty (subject) on any of the results. More pages were revisited using the hierarchical than the relational network structure. However, there were interactions between levels of internet addiction (IAT score) and the type of network. Participants who had lower IAT scores, exposed to hierarchical network, visited a greater proportion of pages, revisited fewer pages, and achieved higher test scores, than lower IAT scorers exposed to the relational network. However, participants with higher IAT scores showed little difference in performance between the networks. There was little impact of IAT score on performance on hierarchical networks, but performance on relational networks improved as IAT scores increased. These data suggest that simple hierarchical networks are better for those with lower internet addiction (as measured by low IAT scores), but there is little difference in network for those with higher internet addiction (higher IAT scores).

Higher education has used digital virtual learning environments (VLEs) as part of their learning strategy for many years [1–4]. This trend has accelerated across the last few years, in part due to recent global pandemic precautions making face-to-face teaching difficult [5,6]. Placing educational information in such digital environments mirrors the general trend for greater use of digital platforms for presenting information. It might be expected that younger individuals would be very familiar with this method of gaining information, and that they would find this aspect of their learning a positive feature [7,8]; however, there remains some debate about this suggestion [7,6], and about the impact of VLEs on learning outcomes [9]. Thus, despite their increasing usage, gaps exist in the knowledge base about the potential impacts of VLEs on learning, which is the major focus of this study.

Although there have been many studies of the efficacy of VLEs for the acquisition of knowledge [9,10], little is known about whether different ways of organising material in VLEs (e.g., in hierarchical or relational structures) differentially impact ability to access and retain information. It is also unknown whether the presence of problematic internet use (PIU; e.g., internet addiction), has an impact on the effectiveness of VLEs. Indeed, it is possible that there will be interactions between levels of internet addiction and favouring differing organisational structures within a VLE. Exploring whether differently structured VLEs differentially impact learning in individuals with greater or lesser PIU could provide important practical information about best practice in structuring the information in such VLEs.

Concerns have been raised about the potential negative impacts of internet addiction across a range of areas of functioning (see [11], for a review). Prevalence of PIU varies depending on the sample and methods used, but it is estimated to manifest in about 7 % of young adults [12]. PIU is often associated with disrupted social functioning, including increased loneliness and social isolation [13,14], increased depression and anxiety [15], as well as altered cognitive function, such as increased impulsivity [16,17]. Although high levels of digital use can have some positive effects on study, such as allowing familiarity with the methods of obtaining information [8,18], such high internet usage also impacts learning negatively [18,19]. For example, higher levels of internet

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addiction reduce levels of intrinsic motivation to study for university students [19]. Although there are a range of concerns about PIU/internet addiction and functioning, including at university, few attempts have examined the relationships between internet addiction and behaviour in controlled VLEs, which was one focus of the current study.

One way in which learning may be impacted is that internet addiction may affect the methods used to obtain information from a virtual network. A browsing strategy is the way in which an individual searches text in a virtual environment, and these strategies may differ between individuals [20,10]. This is a difficult thing to assess, and can be done by complex analyses of real-world web use [21]. However, such studies often lack strong control making their precise interpretation difficult. In contrast, a study by Graff [10] reports use of artificial networks where the structure (relationship between webpages) is known and controlled, and notes that indices such as the number of pages visited, the proportion of total pages visited, and the proportion of pages revisited can be used to describe an individual's strategy of searching the VLE for information. The current study will examine the impact of internet addiction, as a measure of PIU, on such browsing (information gathering) strategies in such controlled networks. Previous work has suggested that these strategies can be related to individual differences in cognitive style [20,10], but very little other work has been conducted on this topic, and none in relation to PIU or internet addiction. Moreover, studies of the impact of individual differences have focused on differences in browsing strategies, but they have not examined the extent to which the information is retained, by assessing learning in a post-browsing test, which the current study assessed.

In addition to the impact of individual differences in internet addiction/PIU on browsing strategy and learning outcome, there are multiple ways in which information can be structured and presented in a VLE [10]. For example, the network structure may be hierarchical – in that, the information is structured vertically, with higher nodes containing sub-nodes that give greater and greater levels of detail about that particular topic. In such networks, browsers can move vertically up and down through the system when exploring topics, but they can only explore one topic at a time, and cannot move horizontally between topics. In contrast, networks may have a more complex relational structure, in which it is possible to move between the topics horizontally. Graff [10]. developed models of both such networks, which contained fictional information about a system. The current research employed these artificial networks to see whether internet addiction interacted with the nature of the network structure to affect browsing strategies and learning outcomes. It might be thought that those with greater browsing experience would prefer the relational structures to the simple hierarchical structures, and that this may favour those with higher levels of PIU/IAT [9]. In contrast, it may be that the greater levels of impulsivity seen for those with PIU/IAT would make using relational networks more distracting [16].

In summary, the current study examined the relationship between different VLE architectures and browsing style (defined by numbers and proportions of pages visited and revisited), and the impact on subsequent knowledge of the material contained on those webpages. In addition, the impact of levels of internet addiction on the strategies adopted, and knowledge gained, across the different architectures was examined. These relationships were examined for a range of undergraduate students at university across a range of disciplines. It was hoped that this initial study of learning in controlled networks would offer some insights into bets practices in organising material in VLEs for higher education given the likely range of PIU issues that will exist with a proportion of their consumers.

Method

Participants

Participants were recruited through a purposive sampling strategy to maximize the likelihood that people actively engaged in internet use and study would respond, as these were the participants of most relevance. Participants at a university responded to advertisements placed on social media and e-mail outlining the study. The inclusion criteria were that individuals must be native speakers of English, aged between 18 and 21 years (to reduce variance due to age differences), and undergraduate students at the University. Once they gave informed consent, participants were asked to attend a session conducted in a laboratory. Two hundred participants were recruited (88 male; 103 female; 9 nonbinary), with a mean age of 19.26 (SD $\pm$ 1.16; range = 18–21) years. The participants came from Science (58, 29 %), Social Science (76, 38 %), and Arts (66, 22 %) subjects. G-Power calculations suggested, for 90 % power, using a rejection criterion of $p < .95$, with a medium effect size ($f' = .25$), that 171 participants would be needed for a 2 $\times$ 2 analysis of variance. Ethical approval was obtained from the University Department of Psychology Ethics Committee.

Apparatus

Networks: A specialised program that mimicked a network of internet pages was employed, which had two configurations (see [10]). The hypertext document was set in the format of a historical document about a novel planet containing information that was entirely fictional, and which enabled the participant to be completely naïve of the information given in the task. The hierarchal program allowed participants to search 'down' the chains of pages, getting deeper information on one subject, before going back up the chain to the top. This network was laid out on the basis of four main branches (labelled in the network as zones 1, 2, 3 and 4). This meant that the participant could only investigate one chain, or zone, at a time. The relational structure allowed participants to search across chains of information as well as down. This meant they could jump from a certain page in zone 1, to another in zone 3, then back to zone 1. Both of the hypertext structures contained sixty-four pages, the hierarchical structure containing sixty-two links, and the relational sixty-two plus additional lateral links related to the content. The participants could navigate through the hypertexts by clicking on the hyperlinks embedded in the texts. Fig. 1 presents a schematic representation of the two types of networks.

Learning test: Twenty-five, four-item multiple choice questions, in relation to the information from the hypertext, were used. These questions were developed by the authors on the basis of their academic expertise, as a result of reading the material in the networks and developing questions that covered much of the material. In this sense, it mirrored an assessment processes that would be given for an undergraduate module. This gave a score of 0 to 25, which was converted to a percentage.

Internet Addiction Test (IAT; Young [22]) is a 20-item scale covering the degree to which use of internet disrupts everyday life (work, sleep, relationships, etc.). Each item is scored on a 1–4 scale, and the overall score ranges from 20 to 100. Young [22] suggested that a score of 40 or greater represents problematic levels of internet usage (see also Hardie & Tee [23]; Romano et al. [24]). The internal reliability of the scale for this sample was .93.

Procedure

Once a participant read the information sheet, and consented, they were tested individually in a quiet experimental room. They were seated at a desk, 5 feet from the experimenter. Placed upon the participant's desk was a computer with a monitor, allowing the participant to see the starting webpage in the network. Participants were instructed that they had 30 min to read and understand as much of the network as possible, and to prepare themselves for a 25-question, multiple-choice test relating to the information that they had just read. They were advised that they may move around the network by clicking on the hyperlinks embedded in text, but they received no further indication of how they

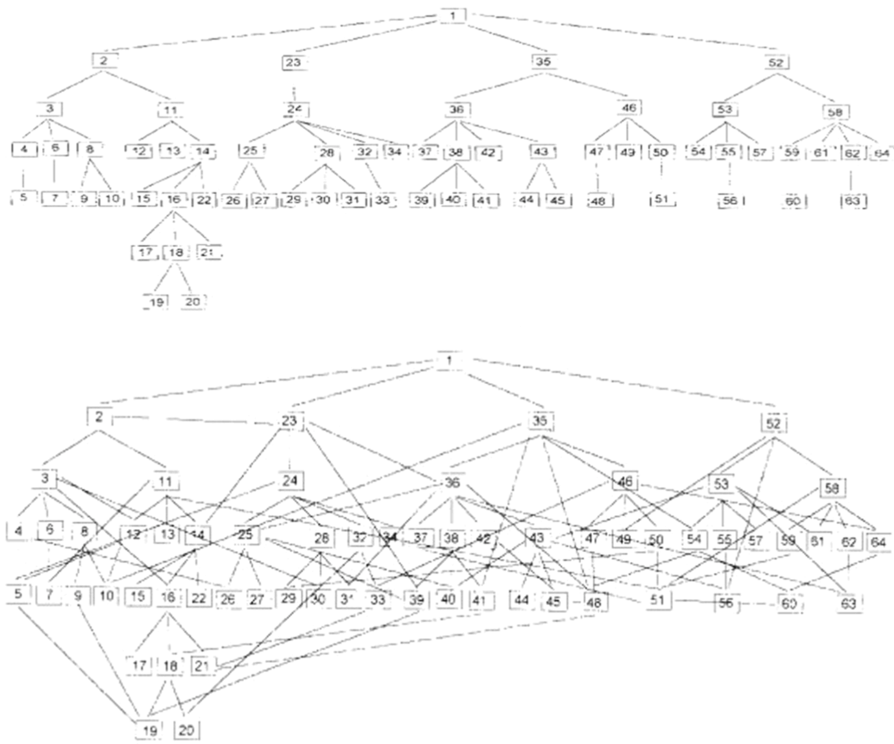

Fig. 1. Schematic representation of a hierarchical (top panel) and relational (bottom panel) network.

were supposed to explore the network. The exploration period then commenced. If participants asked any questions pertaining to the programme, or how to use it during the experiment, the experimenter provided help not relating to the content.

After 30 min, participants were told to stop reading and moving through the network, and the monitor was set to standby. Participants were then asked to complete the IAT, and were asked report how much time they spent on the internet during each of the last three weeks in hours. After 10 min, the participants were given the test on the content of the network. They were given 25 min to complete the 25 items. The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Results

Table 1 shows for both networks the mean (standard deviation) number of pages visited, mean proportion of pages visited, mean number of pages revisited, and mean test scores for the different subjects (Science, Social Science, Arts). Inspection of these data reveals little difference in browsing strategies, or test outcome, across the different subject types (Science, Social Science, Arts). However, participants using the hierarchical network structure visited more pages, visited a greater proportion of the pages, and revisited the pages more often, than those using the relational network.

A two-factor between-subject multivariate analysis of variance (MANOVA) conducted on the three browsing indices, with subject (Science x Social Science x Arts) and network (hierarchical x relational) as factors, revealed a significant main effect of network, *Pillai's Trace* = .329, $F(3192) = 31.35$, $p < .001$, $\eta_p^2 = .329$, but no main effect of subject, *Pillai's Trace* = .016, $F < 1$, $\eta_p^2 = .008$, and no interaction between the two factors, *Pillai's Trace* = .007, $F < 1$, $\eta_p^2 = .003$. Separate two-factor between-subject analyses of variance (ANOVA), with network and subject as factors, revealed significantly higher scores for the hierarchical network compared to the relational network for: number of pages visited, $F(1194) = 8.09$, $p = .005$, $\eta_p^2 = .040$; proportion of pages visited, $F(1194) = 16.49$, $p < .001$, $\eta_p^2 = .078$; and proportion of pages revisited, $F(1194) = 6.98$, $p = .009$, $\eta_p^2 = .035$. None of the analyses produced a significant main effect of subject, all *F*s < 1, nor a significant interaction, all *F*s < 1.

The test scores were also higher for the hierarchical network structure, but similar across the three subjects (Science, Social Science, Arts). A two-factor between-subject ANOVA (network x subject) revealed this effect of network to be significant, $F(1194) = 3.09$, $p = .016$, $\eta_p^2 = .016$, but there was no main effect of subject nor an interaction, both *F*s < 1.

The mean internet addiction score (IAT) for the sample was 33.00 (± 16.03; range = 8–64). The mean IAT for Science students was 35.45 (± 16.83; range = 8–64), Social Science was 32.00 (± 14.36; range = 8–63); and Arts was 31.99 (± 17.13; range = 8–64). A between-subject ANOVA revealed no difference between these scores, $F < 1$, $\eta_p^2 = .01$. Of the sample 60 (30 %) scored above the cut-off for moderate interaction addiction (IAT = 40), with no difference between the three subjects, $X^2 < 1$. The mean amount of time per week spent on the internet for the

Table 1
Results from Experiment 1. Mean number of pages visited (standard deviation), proportion of pages visited, proportion of pages revisited, and test scores, for the different subjects, in both networks.

	Pages visited		Proportion pages visited		Proportion pages revisited		Test score (%)	
	H	R	H	R	H	R	H	R
Science	64.14 (18.62)	56.43 (20.23)	.49 (.11)	.43 (.11)	.57 (.14)	.51 (.10)	47.64 (13.20)	42.66 (14.37)
Social science	64.79 (19.91)	55.03 (19.74)	.47 (.10)	.44 (.11)	.57 (.14)	.53 (.10)	47.48 (13.20)	46.70 (13.76)
Arts	64.21 (20.03)	57.97 (18.37)	.50 (.08)	.45 (.09)	.55 (.15)	.51 (.09)	50.18 (13.71)	45.63 (13.01)

sample was 24.11 (± 5.65; range = 14–35) hours. The mean for Science students was 23.98 (± 5.32; range = 14–35), Social Science was 24.69 (± 5.56; range = 14–34); and Arts was 23.53 (± 6.06; range = 14–35). A between-subject ANOVA revealed no difference between these scores, $F < 1$, $\eta_p^2 = .008$. There was a small positive correlation between internet addiction and internet use, $r = .251$, $p < .001$.

Fig. 2 shows the relationship between internet addiction test (IAT) scores and number of pages visited (top), proportion of pages visited (middle), and proportion of pages revisited (bottom), as a function of the networks (hierarchical versus relational), controlling for internet use (time). Inspection of the top panel of Fig. 2 reveals that the number of pages visited was typically higher in the hierarchical network than in the relational network. However, this was impacted by IAT score, as the number of pages visited decreased as function of IAT score with the hierarchal structure, but this increased as a function of IAT score in the relational structure network. A moderation analysis was conducted using model 1 in PROCESS v.35 [25], with IAT score as a predictor, pages visited as the outcome, network type as moderator, and internet use time as a covariate. This analysis revealed a significant model, $R^2 = .17$, $F(4195) = 1.06$, $p < .001$, with significant effects of IAT score ($\beta = -1.167$, $t = 9.09$, $p = .002$; -1.767:$-.567$), network ($\beta = -39.523$, $t = 5.37$, $p < .001$; -54.049:-24.997), and a significant interaction ($\beta = .820$, $t = 4.20$, $p < .001$; .435:1.205). There was a significant negative conditional effect of IAT score in the hierarchical network (*effect* = $-.348$, $t = 2.62$, $p = .009$; $-.608$:$-.086$), but there was a significant positive conditional effect of IAT score in the relational network (*effect* = .473, $t = 3.46$, $p = .007$; .203:.742).

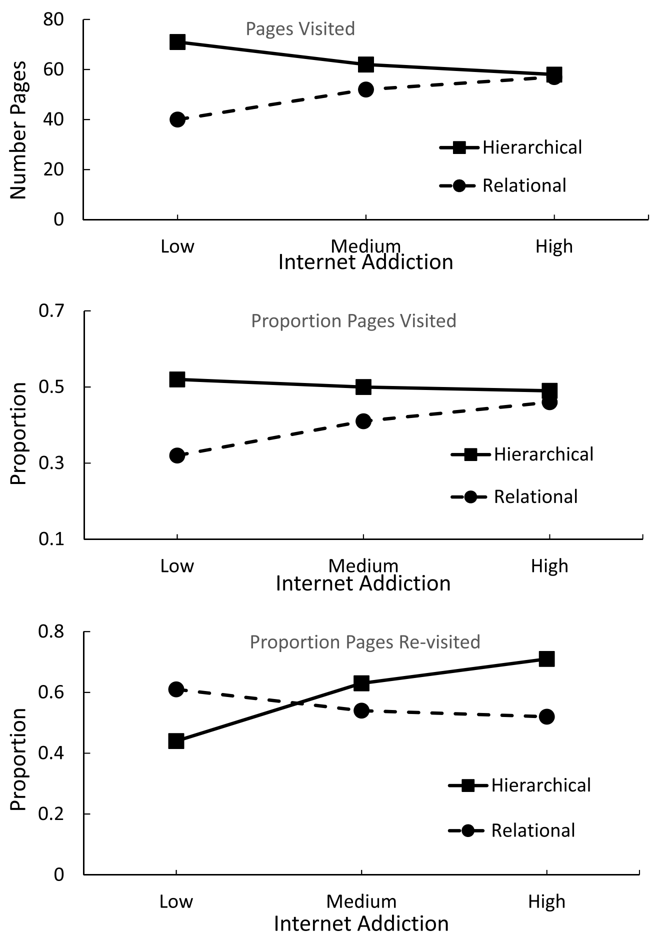

Fig. 2. Relationship between internet addiction scores (1 SD below, at, and above the mean), and number of pages visited (top), proportion of pages visited (middle), and proportion of pages revisited (bottom), as a function of the networks (hierarchical versus relational), controlling for internet use (time) as a covariate.

Inspection of the middle panel of Fig. 2 reveals that the proportion of pages visited was higher for the hierarchical than the relational structure. This figure was constant as function of IAT score with the hierarchal structure, but increased with IAT score in the relational structure network. A moderation analysis, with IAT score as a predictor, proportion of pages visited as the outcome, network type as moderator, and internet use time as a covariate revealed a significant model, $R^2 = .25$, $F(4195) = 16.91$, $p < .001$, with significant effects of IAT score ($\beta = -.005$, $t = 3.61$, $p = .004$; $-.009$:$-.003$), network ($\beta = -.257$, $t = 6.86$, $p < .001$; $-.331$:$-.183$), and a significant interaction ($\beta = .004$, $t = 4.75$, $p < .001$; .003:.007). There was no conditional effect of IAT score in the hierarchical network (*effect* = $-.001$, $t = 1.29$, $p = .196$; $-.002$:.001), but there was a significant positive conditional effect of IAT score in the relational network (*effect* = .004, $t = 5.52$, $p < .001$; .002:.005).

Inspection of the bottom panel of Fig. 2 reveals that the proportion of pages re-visited increased as function of IAT score with the hierarchal structure, but decreased in the relational structure network. A moderation analysis, with IAT score as a predictor, proportion of pages revisited as the outcome, network type as moderator, and internet use time as a covariate revealed a significant model, $R^2 = .43$, $F(4195) = 36.88$, $p < .001$, with significant effects of internet addiction ($\beta = .017$, $t = 1.88$, $p < .001$; .014:.021), network ($\beta = .275$, $t = 7.10$, $p < .001$; .199:.352), and a significant interaction ($\beta = -.010$, $t = 9.73$, $p < .001$; $-.012$:$-.008$). There was a significant positive conditional effect of IAT score in the hierarchical network (*effect* = .007, $t = 1.66$, $p < .001$; .006:.009), but there was a significant negative conditional effect of IAT score in the relational network (*effect* = $-.003$, $t = 3.57$, $p < .001$; $-.004$:$-.001$).

Fig. 3 shows the relationship between internet addiction test (IAT) scores and test scores, as a function of the networks (hierarchical versus relational), controlling for internet use (time). These data reveal that test scores tended to be higher for the hierarchal structure. They remained largely constant as a function of IAT score for that hierarchal network, but increased as a function of IAT scores for the relational network. A moderation analysis (model 1, PROCESS v.35), with IAT score as a predictor, test scores as the outcome, network type as moderator, and internet use time as a covariate revealed a significant model, $R^2 = .15$, $F(4195) = 8.54$, $p < .001$, with significant effects of IAT score ($\beta = -.581$, $t = 2.70$, $p = .007$; -1.004:$-.157$), network ($\beta = -25.519$, $t = 4.91$, $p < .001$; -35.772:-15.266), and interaction ($\beta = .523$, $t = 3.79$, $p = .002$; .252:.958). There was no conditional effect of IAT score in the hierarchical network (*effect* = $-.057$, $t = .61$, $p > .50$; $-.242$:.127), but there was a significant positive conditional effect of IAT score in the relational

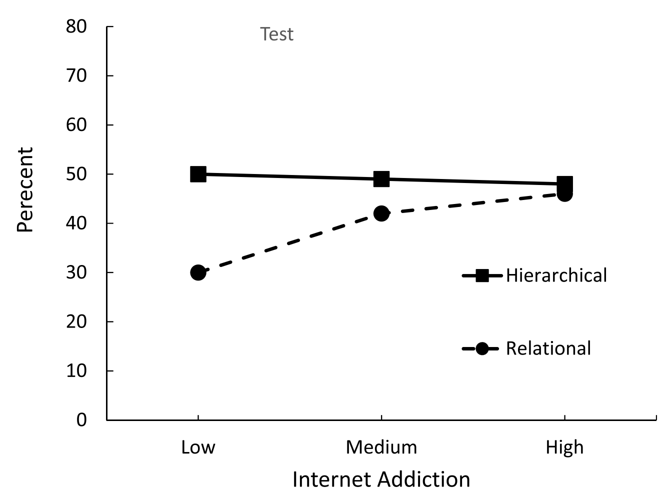

Fig. 3. Relationship between internet addiction scores (1 SD below, at, and above the mean), and test scores, as a function of the networks (hierarchical versus relational), controlling for internet use (time) as a covariate.

network (*effect* = .466, $t = 4.82$, $p < .001$; .275:.656).

Discussion

The current study examined the relationship between different VLE architectures and browsing style and knowledge acquisition with a view to providing important practical information about possible best practices in organising that VLE information. In addition, the impact of internet addiction (as measured by the IAT) on browsing style and knowledge across the different architectures was examined. This was thought important, as both the use of VLE and the incidence of internet addiction/PIU are increasing. In general, more pages were visited, and more knowledge gained, with hierarchical than relational structures. Overall, there was little numerical impact of IAT scores, but IAT scores impacted the effects of the network structures. Those with low IAT scores (lower PIU) accessed more information in simple hierarchical than relational networks, but the difference between the networks diminished as IAT scores increased. Test results followed a similar pattern, with those with lower IAT scores favouring hierarchical networks, with little impact of internet addiction in relational networks.

A key finding for those planning VLEs in higher education is that, overall, simple hierarchical networks tended to facilitate a more efficient browsing strategy and knowledge capture than complex relational structures (although with some impact of IAT/PIU levels). There was no impact of subject studies on any of these results, which suggests a generality across student types. It may also be noted that analyses were conducted for gender on the current data, but in no case did the analyses show any impact of gender whatsoever. This finding is slightly at odds with previous examinations of the impacts of network structure (see [10]). Such investigations reported little overall difference between the networks, although with some impact of individual differences (see also [20]). It should be noted that there are differences between the current study and previous examination, most notably in that the previous studies were conducted nearly 20 years ago, and experience and motivation to use VLEs may well have altered in that period. Nevertheless, an important message may be to keep the structure simple.

Although the main findings suggest that simple hierarchical networks in VLEs may well be more suitable for most individuals, only those with higher IAT scores (higher PIU) benefitted from more complex relational structures. This highlights the importance of considering individual differences in such studies [20,10]. There are a number of possible reasons for these effects. One possibility is that those with higher PIU (as measured by higher IAT scores) also tend to have more experience in using the internet – there is a small positive correlation between IAT scores and time spent on the internet. This would suggest digital experience may play a role in the use of complex network structures [9]. However, the current analyses controlled the effect of time spent on the internet during the week making this less likely as a full explanation.

An alternative suggestion is that the lower levels of motivation that have been reported as being experienced by those with higher internet addition [26], coupled with their increased levels of impulsivity [16], mean that the complexity of the relational network may have held more interest for them. This increased interest may have facilitated their performance on complex relational structures though that mechanism. Whatever the eventual explanation, the results suggest that internet addiction levels will impact learning outcomes in a VLE differentially depending on the architecture of the network.

The practical implications of the work lie in the possible best practice of organising VLE information in a way that is accessible for all. The current data suggest that simple hierarchical structures offer the best hope for easier accessibility and depth of learning. Relational networks were well received by those with higher PIU scores (and probably more experience in using digital technology). However, accessibility of knowledge and learning for most appears greats when structures are simpler. An implication of this form of work is that different personality types, yet to be investigated, may work better with different types of network arraignment. If resources allow, then a choice between structures may enhance the experience of the user.

There are a number of limitations that should be noted concerning the current study. Firstly, the study used an artificial network in a laboratory setting. Although this produces advantages in terms of control of the network, and makes analyses easier than in real world settings (cf. [21]), it is unclear the extent to which these findings may generalise. The current study also focused on a limited age range of participants (18 to 21). This procedure was followed to ensure a reduced variability in the digital backgrounds of the cohort, which may have had an impact. However, it may be that the results would alter with an increased age range, which may be important for institutions focusing on distance learning. In addition, although the purposive sampling strategy maximized the likelihood that people actively engaged in internet use and study would be recruited, it does limit the overall generality of the results. The impact of these issues could be further explored in future studies.

The measure employed in this study (IAT) is now somewhat older than several other tests, and it may be that the questions presented in the IAT may not capture the full complexities and nuances of PIU in a contemporary context. While the IAT remains a well-used, reliable, and validated tool, that certainly captures many aspects of internet addiction, its use may compromise the validity of the results if the broader concept of PIU is considered. There are other personality factors that may well play a role in impacting the use of differently structure VLEs. Of course, not all can be examined at once, but this aspect may be worth further study. As it becomes easier to alter the structures of VLEs, it may be that allowing students the choice of which type of VLE suits them could offer great educational benefits. Moreover, in the current study, the participants' satisfaction scores with two different network structures in VLEs were not assessed. This information could have given some important data for the design of such networks based on individual preferences [27], and such data could be included for collection in any further studies.

In summary, the current study found that the nature of the VLE network impacted the effects of internet addiction (PIU) on browsing style and knowledge acquisition. Overall, there was little impact of internet addiction (IAT scores), but internet addiction scores affected the efficiency of the network structures. Individuals with lower internet addiction scores appeared to find simple hierarchical more effective than relational networks, but there was no difference in the effect of the networks for those with higher internet addiction scores.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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