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Developmental structure of digital maturity

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ABSTRACT

The last decades have seen growing attention for the positive and negative effects of digital technology on adolescent's wellbeing. Large individual variability in these effects is likely caused by individual differences in the way people interact with digital devices. Digital maturity aims to capture the extent to which young individuals use digital technology in a healthy and adaptive way. The recently developed Digital Maturity Inventory (DIMI) uses self-report to measure ten domains, from digital literacy to emotion regulation, that constitute digital maturity of adolescents. To better understand the relative contribution and interplay of the different domains in the development of digital maturity, we employed a moderated psychometric network model. We measured digital maturity scores of 378 participants, aged 9–43 years. The results revealed that support-seeking and the regulation of aggressive impulses are central domains within the network, indicating important starting points for intervention studies. Although age did not moderate the connections within the network, we did find that older participants were more digitally literate and asked less often for support regarding digital issues. These results suggest that digital maturity is a relatively robust concept across adolescence and into adulthood and provide important footholds for interventions.

1. Introduction

The role of digital technology in our daily life has increased strongly over the past few years. Unsurprisingly, this caused an increase in the time people spend online. A survey from 2021 showed that 85% of American adults go online daily and that only 7% does not use the internet at all (Pew Research Center, 2021). Digital device use is expected to increase even more, as adolescents' time spent online and smartphone use has increased significantly in the last years (Smahel et al., 2020; Twenge, Martin, & Spitzberg, 2018). This development has initiated a wide range of research into the effects of digital technology use. For example, the use of digital technology has been associated with safety and privacy concerns (Livingstone et al., 2017, pp. 2015–2017) and mental health issues including cyberbullying (Giumetti & Kowalski, 2022), excessive use or addiction, sleep dysfunction (Bae, 2017; Billieux et al., 2015; Dresp-Langley & Hutt, 2022) and even impaired brain development (Small et al., 2020). In contrast, the use of digital technology can also increase problem-solving skills and creative thinking (Fitton, Ahmedani, Harold, & Shifflet, 2013; Oldham & Da Silva, 2015), improve educational outcomes (Lin, Chen, & Liu, 2017; Islam, Wu, Cao, Alam, & Li, 2019) and facilitate economic growth and access to and interaction with others (Hayes, James, Barn, & Watling, 2022; Solomon & van Klyton, 2020). Although most work has focused on establishing a relationship between digital (media) use and mental health issues in especially adolescents (Appel, Marker, & Gnambs, 2020; Bell, Bishop, & Przybylski, 2015; Twenge, Joiner, Rogers, & Martin, 2018; Valkenburg, Beyens, Meier, & vanden Abeele, 2022), no such relationship has been established robustly (Odgers & Jensen, 2020; Orben, 2020; Orben & Przybylski, 2019; Valkenburg, Meier, & Beyens, 2022).

Recently, researchers have identified several issues that have hampered progress in the field, which can be summarized as the need for more detailed data on individual differences in the way people use digital devices (Sultan, Scholz, & van den Bos, 2023). For example, both low and excessive but not moderate digital and social media use have been associated with low well-being, as has passive but not active use (Dienlin & Johannes, 2020; Przybylski, Orben, & Weinstein, 2020). However, a recent review demonstrated that a course division between active and passive users is insufficient to establish a robust relationship between social media use and measures of well-being (Valkenburg, van Driel, & Beyens, 2022). Therefore, researchers need to better understand individual differences by taking into account the content of social media or digital use. Two possible approaches are studying trace data or

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experience-sampling self-reports (Sultan et al., 2023; Verbeij, Pouwels, Beyens, & Valkenburg, 2022) and studying pre-existing capacities or characteristics of the users, such as their personalities, capacities, mood or neurobiological factors (Liu & Baumeister, 2016; Westbrook et al., 2021). For example, the Digital Maturity Inventory (DIMI) has recently been developed that introduces the concept of digital maturity as a novel way to look at adolescents' digital technology use, based on findings that the mature use of digital devices not only depends on the frequency of use, but also on personality traits and psychosocial growth (Laaber, Florack, Koch, & Hubert, 2023). The authors therefore describe digital maturity as a set of capabilities and attitudes that facilitate a responsible way to use digital technologies by supporting individual development and social adjustment.

Here, we focus on individual and developmental differences in users in terms of digital maturity. The DIMI encompasses a set of ten domains relating to a self-determined way of using digital devices, mastering digital skills and the interaction with the social environment. Examples of domains are digital literacy, autonomous choice to use digital devices, support-seeking and the regulation of negative emotions or impulses. Cronbach's alphas of all ten dimensions have been shown to exceed 70%, indicating acceptable to good internal consistency. Importantly, the DIMI has been demonstrated to negatively correlate with the amount of mobile device use and to be linked to traits reflecting personality maturity (i.e. emotional stability, conscientiousness and agreeableness), thereby embedding the concept of digital maturity in psychosocial personality development. Overall digital maturity is computed as the weighted sum of all individual domain scores, as is a common procedure in psychometrics (e.g. Big Five personality, self-esteem). However, this aggregated score gives little insight into how the individual domains are structured and interconnected. Here, we aim to gain more insight into the structure of digital maturity by applying a network analysis.

Network theory has rapidly become important in various fields of behavioral science, including social science (Borgatti, Mehra, Brass, & Labianca, 2009), psychopathology (Boschloo, van Borkulo, Borsboom, & Schroevers, 2016; McNally et al., 2015), personality dynamics (Costantini et al., 2019), political attitudes (Dalege, Borsboom, van Harreveld, & van der Maas, 2017) and behavioral interventions (Chambon et al., 2022). Network theory assumes that complex and dynamic systems are modelled as a configuration of observable variables or nodes, which are connected with each other by edges that represent pairwise interactions. This is in contrast to more traditional psychometric models such as principal component analysis, in which a dataset is reduced to fewer dimensions with loadings signifying the covariances between the observed variables and the components, or factor models, in which the covariance between variables results from the influence of a common latent, unobserved variable. For example, in psychiatry, the idea is that disorders are networks of symptoms and causal relations between them, rather than the symptoms being a measure of an underlying (latent) variable (Borsboom, 2008; Cramer, Waldorp, van Der Maas, & Borsboom, 2010; Van Der Maas et al., 2006). A key advantage of a network approach is that it can inform us about potential interventions, by targeting central nodes in the network that will likely have the largest impact on the entire network (Chambon et al., 2022; Stocker et al., 2023). For example, interventions targeted at a central node within a large COVID-19 attitude network – trust in authorities and health care professionals – successfully affected other, downstream nodes (e.g. vaccination intention), whereas interventions targeted at a more peripheral node – perceived social norms about compliance with safety measures – yielded little effect beyond the target node (Chambon et al., 2022).

In the current study, we use a network approach to assess how the different digital maturity domains are interconnected. For example, it can be expected that emotion regulation and autonomy over content are related domains, whereas they have little to do with one's knowledge about secure password usage. Moreover, the DIMI has been specifically developed and tested for an adolescent age group between 12 and 18 years old. As smartphone use and online communication are especially central to the daily lives of young age groups, who are therefore more prone to develop problematic use (Livingstone & Bober, 2005; Pew Research Center, 2022; Thayer & Ray, 2006), we additionally explore how the network structure develops from adolescence into adulthood. It can be expected that scores on individual domains such as regulation of negative emotions and digital literacy increase, and support-seeking decreases over age. However, if and how age moderates the connections between the domains is still an open question. For example, for younger adolescents, digital literacy might be strongly related to support seeking, whereas it is more strongly related to digital risk perception for older individuals. Alternatively, literacy might be very central to the network for younger adolescents, with many connections with other domains, whereas for older individuals, using mobile devices for civic engagement or personal growth might be more central. The results of these analyses can thus identify which domains are most central to digital maturity as a whole and could therefore be targeted by interventions, while also informing us about how these interventions would in turn affect other domains. Examining if and how this changes across age serves to most effectively facilitate a responsible way to use digital devices for different age groups.

2. Methods

2.1. Participants

The current data analysis is based on data from two different studies in Germany and the Netherlands that included behavioral and fMRI tasks not reported here, in which a total of 378 volunteers participated (202 female; age: 9–43 years, mean = 15.9, SD = 6.7; Fig. 1A). Participants aged 9–16 were recruited from a participant pool at the Max Planck Institute for Human Development in Berlin (Germany) that includes approximately 3000 participants (N = 273, 140 female; age: mean = 12.2, SD = 2.2), whereas participants 22–43 were recruited by the University of Amsterdam (The Netherlands) through posters at sports clubs in the vicinity of the university and Instagram advertisements targeted at individuals in the region of Amsterdam (N = 105, 62 female; age: mean = 25.5, SD = 4.5. These datasets were pooled to allow for a more reliable sample size and for the exploration of age effects across a broader range of ages. Once a potential participant signed up for the study online, they filled in a questionnaire to determine their eligibility for the study, including that they were psychologically healthy, fell within the age range, and were proficient in German or Dutch, respectively, before they could participate. All participants gave written or online informed consent. For participants who were below 18 years old, additional informed consent was provided by one of their parents. All procedures were approved by the Ethics Review Board of the respective universities. Participants were compensated based on an hourly rate of €10.

2.2. Measures and procedures

To measure digital maturity, participants filled in the recently developed Digital Maturity Inventory (DIMI). This self-report instrument measures digital maturity in ten different domains: Autonomous Choice to Use Mobile Devices, Autonomy Within Digital Contexts, Digital Literacy, Individual Growth in Digital Contexts, Digital Risk Awareness, Support-seeking Regarding Digital Problems, Regulation of Negative Emotions in Digital Contexts, Regulation of Impulses in Digital Contexts, Respect Towards Others in Digital Contexts and Digital Citizenship. Each domain is represented by three to four items, with a total of 32 items, to which participants respond on a 5-point scale. Example items are: *When using a mobile device, I choose the context I want to see (1 = Never, 5 = Always)* and *I know how to adjust the privacy settings of social media sites (for example, Instagram, Snapchat, TikTok) (1 = Not at all true for me; 5 = Very true for me)*. Participants in The Netherlands completed

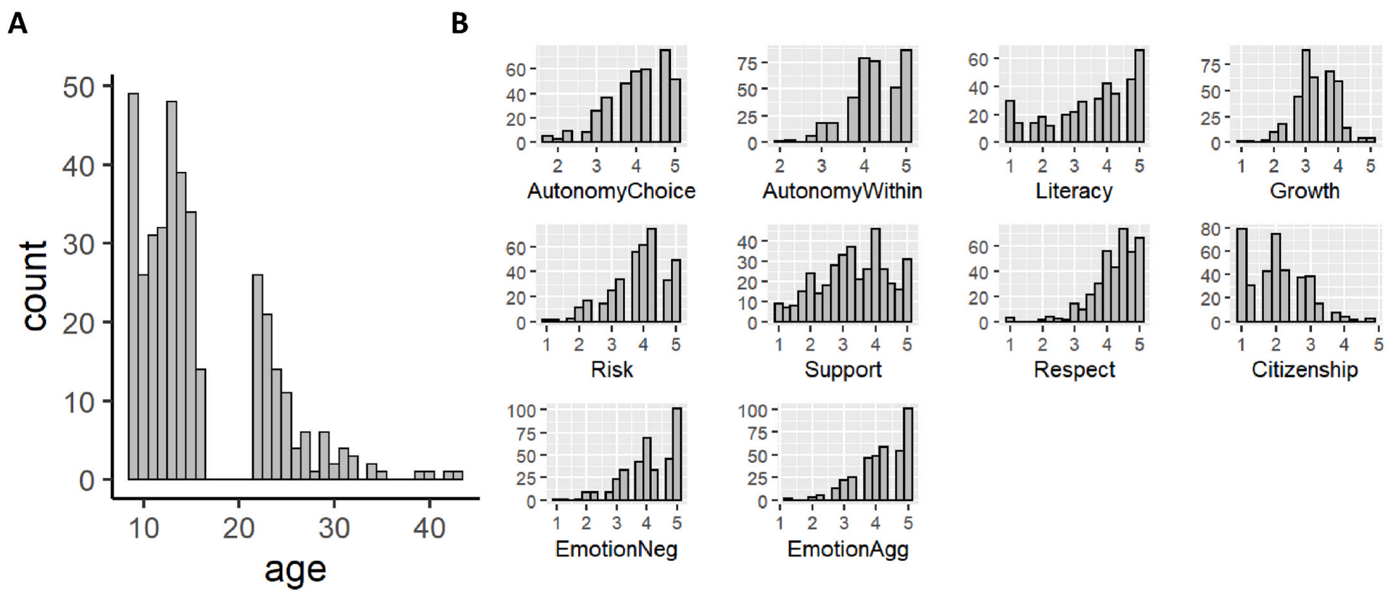

Fig. 1. A – Histogram of age distribution across all participants. **B** - Histograms of digital maturity scores per domain.

a Dutch version of the DIMI online, whereas participants in Germany completed a German version of the DIMI on site. Completion of the DIMI took on average five to 10 min (see supplementary material S1 for the complete DIMI in English).

2.3. *Data analysis*

All analyses were conducted in R version 4.0.4 (R Core Team, 2021). Responses were first converted to numerical values ranging from 1 to 5. Values for the items within the domains Autonomous Choice to Use Mobile Devices, Regulation of Negative Emotions in Digital Contexts and Regulation of Impulses in Digital Contexts were reverse coded, so that higher scores always indicated higher digital maturity. The mean score for each domain was then calculated by averaging all three to four responses within each specific domain, resulting in 10 domain scores per participant. In this sample, the internal consistency of the domains ranged from acceptable (Cronbach's alpha ≥0.7) to excellent (Cronbach's alpha ≥0.9; Table 1). Table 1 and Fig. 1B show the distributions of and correlations among the domains.

Network analysis. The network analysis consisted of the following steps: 1) estimating the edges, 2) visualizing of the network, 3) assessing the stability of the edges and 4) assessing node centrality.

Estimating the edges. To examine how the separate digital maturity domains are interrelated (research question 1) and how this is potentially moderated by age (research question 2), we used the *mgm* package version 1.2–13 to estimate a moderated network model (Haslbeck, Borsboom, & Waldorp, 2021). We first ran the function mgm() to estimate all pairwise linear relationships between the digital maturity domains. We then ran the same function, but added age as a moderator to the model, to additionally estimate all three-way interactions between digital maturity domains and age. The estimation is performed using L1 regularization, or Lasso regression, which shrinks small parameter estimates to zero and only presents the most robust estimates, thereby simplifying the interpretation of the resulting model, which is useful in the case of many parameters. The strength of the L1 regularization, or the extent to which parameters are shrunk to zero, is controlled by the tuning parameter λ, which is selected based on the extended Bayesian Information Criterion (EBIC). This EBIC has a hyperparameter γ, which controls a penalization for model complexity, and which was kept at the default value of 0.25 (Epskamp, 2016). The regression analysis returns two directional parameter estimates for each pairwise interaction (B predicting A; A predicting B), and three directional estimates for each three-way interaction (or moderation; C predicting the interaction between A and B; A predicting the interaction between B and C; B predicting the interaction between A and C). Using the AND-rule of the mgm function, we specified that these are averaged to a single undirected estimate only when all directed estimates are non-zero. If one of the directed estimates is zero, the undirected estimate is also set to zero. All variables are automatically standardized with a mean of 0 and a standard deviation of 1, to i) ensure that the regularization of the parameters does not depend on standard deviation of the variables and to ii) help with model interpretation because all intercepts are set to zero.

Visualizing the network. The moderated network models are visualized using the function FactorGraph() from the *mgm* package, which shows green (red) edges for parameter estimates with positive (negative) sign, and additional nodes for any three-way interactions.

Assessing the stability of the edges. The distributions of many of the variables included in the model are skewed (Fig. 1) and would therefore most likely violate the assumption of normally distributed residuals. Rather than transforming these variables, which would complicate the interpretation of the parameters, we opted to use a bootstrapping procedure to assess the stability of the parameter estimates and thus the robustness of the model (Haslbeck, 2019).[1] The resample() function from the *mgm* package was used to run 1000 bootstrapped samples, and the summary of the sampling distributions was visualized using the plotRes() function.

Assessing node centrality. We additionally assessed the network structures with an index of strength centrality (Dalege, Borsboom, van Harreveld, & van der Maas, 2017), which is calculated as the sum of the absolute edge values connected to a particular domain, thus indicating to what extent the domain serves as a hub in the network. Strength centrality was analyzed using the centralityPlot() function from the package *qgraph* version 1.9.2 (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012).

[1] Normalizing the variables using a non-paranormal transformation, as implemented in the *huge* package version 1.3.5 (Jiang et al., 2021), yielded no qualitative differences compared with using non-transformed data.

Table 1
Means (M), standard deviations (SD), Cronbach's alpha and Pearson's correlations of the DIMI domains.

Domain	*M*	*SD*	*Cronbach'salpha*	Autonomy Choice	Autonomy Within	Literacy	Growth	Risk	Emotion Neg	Emotion Agg	Support	Respect
Autonomous Choice to Use Mobile Devices	4.03	0.76	0.72	–								
Autonomy Within Digital Contexts	4.23	0.63	0.71	0.14[b]	–							
Digital Literacy	3.51	1.29	0.93	−0.27[c]	0.02	–						
Individual Growth in Digital Contexts	3.31	0.62	0.87	−0.06	0.19[c]	0.07	–					
Digital Risk Awareness	3.87	0.82	0.92	0.26[c]	0.20[c]	−0.06	0.12[a]	–				
Regulation of Negative Emotions in Digital Contexts	4.08	0.84	0.84	0.28[c]	0.14[b]	0.09	0.06	0.05	–			
Regulation of Impulses in Digital Contexts	4.17	0.77	0.73	0.28[c]	0.05	−0.03	−0.05	0.18[c]	0.34[c]	–		
Support-seeking Regarding Digital Problems	3.33	1.06	0.92	0.22[c]	0.22[c]	−0.39[c]	0.10	0.26[c]	−0.03	0.02	–	
Respect Towards Others in Digital Contexts	4.25	0.67	0.85	0.14[b]	0.16[b]	0.11[a]	0.06	0.37[c]	0.11[a]	0.34[c]	0.17[c]	–
Digital Citizenship	2.03	0.80	0.91	−0.13[a]	−0.02	0.21[c]	0.19[c]	0.03	−0.15[b]	−0.08	−0.09	0.13[a]

[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

3. Results

3.1. Network structure of digital maturity

The network of pairwise relationships between the ten domains of digital maturity was estimated as depicted in Fig. 2A. Each edge represents a statistical undirected relationship between two domains, or nodes within the network. The thicker the edges, the stronger the relationship. Fig. S1 depicts the stability of the estimated edges, including the proportion of bootstrap samples for which the parameter had been estimated to be non-zero, and the 95% confidence intervals of the estimates. We will focus only on edge weights that were estimated to be non-zero in all or nearly all (>90%) of the bootstrap samples and can thus be considered to be more robust, although we visualize all edges resulting from the original sample to facilitate insight into the sub-threshold relationships within the network and to more easily link the results to the centrality scores of the domains. We report the edge weights of the original sample, along with the 95% confidence intervals of the edge weights across the 1000 bootstrap samples. Importantly, the specific values of the estimates varied substantially across the bootstrap samples and should thus be interpreted cautiously.

A qualitative, visual inspection reveals a strong subcluster on the upper side of the graph, in which Digital Literacy (Ltr) was negatively related with Autonomous Choice to Use Mobile Devices (Au_C; −0.17,

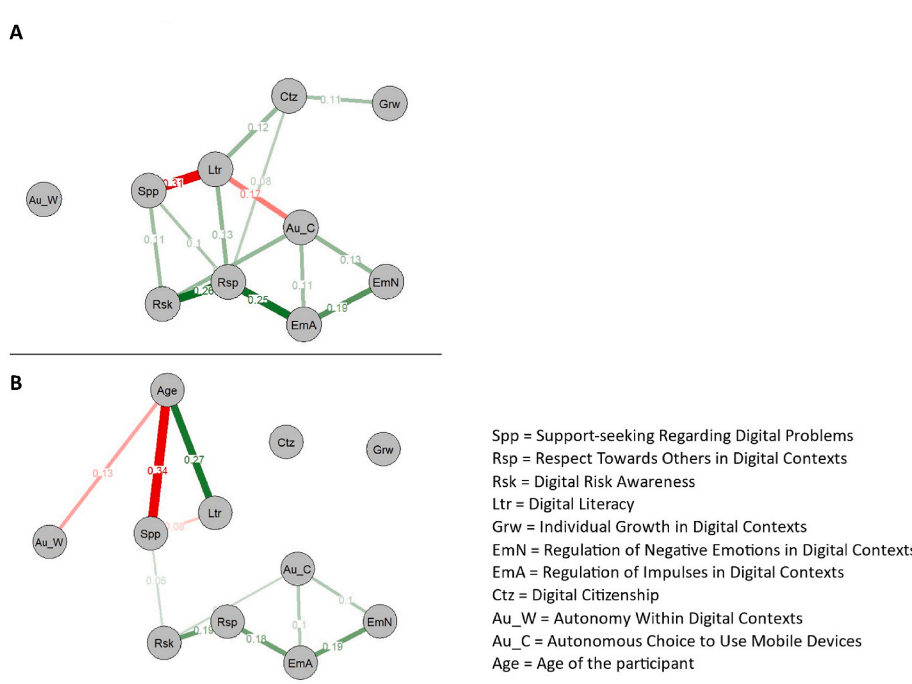

Fig. 2. Network structure for Digital Maturity. Positive associations are represented as green edges; negative associations are represented as red edges. Edge thickness represents the strength of the parameter estimate, which is the partial correlation between the domains it connects. **A** – Network structure for Digital Maturity without age. **B** – Network structure for Digital Maturity including age as a moderator variable.

95% CI = [−0.26, −0.08]) and Support-seeking Regarding Digital Problems (Spp; −0.31, 95% CI = [−0.40, −0.25]). This indicates that the more literate an individual was, the less they felt like they make a conscious decision to go online and the less they asked for help.

On the lower side of the graph, we see a strongly connected subcluster, including the Regulation of Negative Emotions (EmN), the Regulation of Impulses (EmA), Respect towards Others (Rsp) and Risk Awareness (Rsk). On average, individuals who were better able to regulate their impulses were also better at regulating their negative emotions when something upset them online (0.19, 95% CI = [0.13, 0.29]), and tended to show more respect towards others (0.25, 95% CI = [0.14, 0.32]). Moreover, those who showed more respect also demonstrated higher risk awareness (0.26, 95% CI = [0.15, 0.33]). All of these domains, except for Respect toward others, were also positively connected with Autonomous Choice to Use Mobile Devices (Regulation of negative emotions: 0.13 95%, CI = [0.00, 0.27], Regulation of impulses: 0.11, 95% CI = [0.00, 0.20], Risk awareness: 0.12, 95% CI = [0.00, 0.20]), meaning that the more these individuals made a more conscious decision about whether or not to go online, rather than having the feeling that they have to be online because they would otherwise miss out of something. Interestingly, Autonomy Within Digital Contexts (Au_W), thus making conscious decisions about the specific content of their online environment, did not seem to be significantly related to any other domain. Finally, Support-seeking was positively related to Risk Awareness (0.11, 95% CI = [0.00, 0.19]), indicating that individuals who ask others for help were on average more aware of the risks of digital environments.

3.2. The role of age within the digital maturity network

Adding age to the network model led to a similar structure of digital maturity, although there are some noteworthy differences (Fig. 2B; Fig. S2 for edge stability). First of all, age did not moderate the pairwise interactions between the domain scores of digital maturity, indicating that the overall structure of digital maturity was equivalent across all ages included in the current study (9–43). Age itself was positively associated with Digital Literacy (0.27, 95% CI = [0.23, 0.41]) and negatively associated with Support-seeking (−0.34, 95% CI = [−0.40, −0.25]), meaning that older individuals are more literate and ask for help less often (For reference, simple Pearson's correlations between DIMI domain scores and age can be found in Fig. 3). At the same time, the direct negative relationship between Digital Literacy and Support-seeking strongly decreased after adding age to the model (−0.08, 95% CI = [−0.18, 0.00]). Moreover, the negative relationship that was previously present between Digital Literacy and Autonomous Choice to Use Mobile Devices has now disappeared from the network.

The subcluster that was found earlier for Regulation of Negative Emotions, Regulation of Impulses, Respect towards Others and Risk Awareness is still present after the inclusion of age (Relationship between Regulation of Impulses and Regulation of Negative Emotions: 0.19, 95% CI = [0.11, 0.26], Relationship between Regulation of Impulses and Respect towards Others: 0.18, 95% CI = [0.11, 0.30], Relationship between Respect towards Others and Risk Awareness: 0.19, 95% CI = [0.12, 0.31]). However, the interconnectedness of this cluster with Autonomous Choice to Use Mobile Devices has diminished (Regulation of negative emotions: 0.10 95%, CI = [0.00, 0.21], Regulation of impulses: 0.10, 95% CI = [0.00, 0.18], Risk awareness: 0.07, 95% CI = [0.00, 0.15]). Finally, the positive association between Support-seeking and Risk Awareness has become weaker (0.06, 95% CI = [0.00, 0.14]).

3.2.1. Robustness of age effects

To explore if any moderating effects of age could be specific to adolescence and would therefore only emerge when testing this specific group, we reran the moderated network analysis on 9–16 year old participants only. Again, age did not moderate any of the pairwise interaction between the DIMI domains (Figs. S3–4). Finally, we split our data set into 9–16 year olds and 22–43 year olds to check if any age effects could be uncovered when comparing an adolescent versus an adult group. We performed permutations tests on group differences between the adolescent and adult networks using the NCT() function from the *NetworkComparisonTest* package (van Borkulo et al., 2022). This revealed that there was neither a difference in overall network structure, with the maximum difference in edge weights being 0.17 ($p = .953$), nor a difference in global network strength – the absolute sum of all edges in the network (0.34, $p = .991$).

3.3. Network centrality

The centrality of domains within a network can be measured by strength, which indicates the sum of the absolute edge weights that directly connect a node to all other nodes. Strength centrality thereby

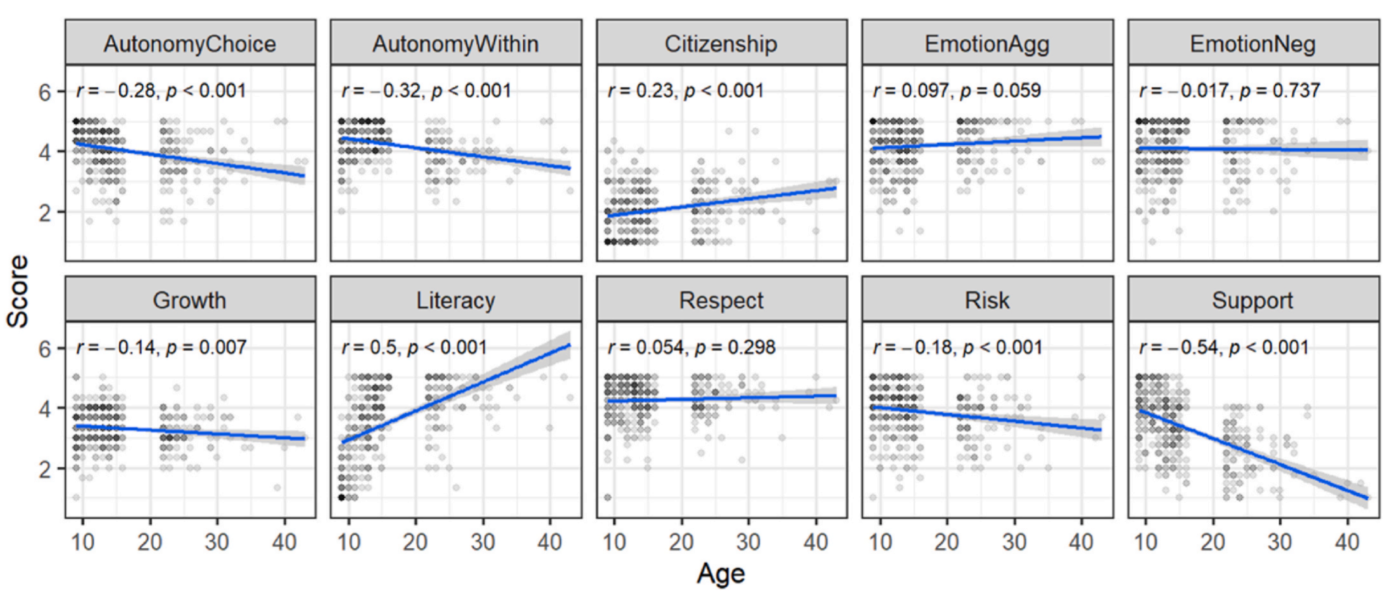

Fig. 3. Simple Pearson's correlations between DIMI domains and age. Note that these simple pairwise correlations are roughly in line with the parameters estimated by the moderated network analysis, which can be interpreted as partial correlations.

conveys a summary score of how strongly that domain is related with the other domains in the network. Note that the strength score for a domain can be high when that domain is weakly correlated with many other domains as well as when the domain is highly correlated with only a few other domains. Strength centrality for both the network without (blue) and with age (black) is depicted in Fig. 4. In the network without age, Respect towards Others and Digital Literacy had the highest strength centrality scores, implying that these domains play an important role within the network. This can also be observed in the network structure (Fig. 2A), where both Respect towards Other and Digital Literacy are strongly correlated, either positively or negatively, with other domains. These domains were followed by the strength scores for Regulation of Impulses, Autonomous Choice to Use Mobile Devices, Support-Seeking and Risk Awareness. Individual Growth (Grw) and Autonomy Within Digital Contexts had the lowest strength scores, in line with their (near) disconnectedness in the network. When age was added to the network model, overall strength centrality decreased, with fewer interconnections between the digital maturity domains, particularly for Respect towards Others and Digital Literacy decreased. Support-seeking and Regulation of Impulses still scored relatively high in terms of centrality. Concurrently, age itself had the highest strength centrality score, suggesting a pivotal role in the structure of digital maturity.

3.4. Follow-up comparison between Dutch and German adults

Our original sample included German youth (N = 273) and Dutch adults (N = 105), meaning that our results, specifically any results regarding age, could in principle be confounded by country. We therefore recruited an additional sample of 105 German adults and combined this adult sample with the original German youth sample (total N = 378) and recomputed the network structure, with and without a moderation by age. To assess whether the inclusion of German rather than Dutch adults warranted a different interpretation of the network structure, we performed permutations tests on group differences between the original networks and the new German networks using the NCT() function from the *NetworkComparisonTest* package. Despite the fact that the German and Dutch adult samples differed substantially in terms of average domain scores (Table S1), the resulting networks remained statistically invariant (Fig. S5), supporting the notion that possible country differences between the Netherlands and Germany did not play a role in the network structure of digital maturity (See Supplementary Methods and Results for more details).

4. Discussion

The concept of digital maturity has recently been introduced as a responsible way to use digital technologies by supporting individual development and social adjustment. The newly developed Digital Maturity Inventory (DIMI) indexes ten domains that are postulated to constitute digital maturity in adolescence. However, little is known about how these domains are structured and interconnected. The aim of the current study was to employ a moderated network analysis to advance our understanding of digital maturity and how its structure develops from adolescence into adulthood.

Our network analysis revealed two robust but distinct subclusters of digital maturity. A first cluster that could be identified pertained to digital skills and problem solving, and included Digital Literacy and Support-seeking Regarding Digital Problems, which negatively correlated with each other, and which seemed to be mediated by age. On average, older individuals reported to have better knowledge of digital systems, corresponding with a lower need to ask for help. The finding that Support-seeking was relatively central to digital maturity as a whole dovetails with prior research establishing that internet-related parental communication relates to positive online behavior and reduced online risks (Duerager & Livingstone, 2012; Holtz & Appel, 2011; Lee & Chae, 2007) and can even modulate the impact of extensive internet use on loneliness (Appel, Holtz, Stiglbauer, & Batinic, 2012).

Secondly, a robust cluster emerged that encompassed the Regulation of Negative Emotions and Impulses, Respect towards Other and Risk Awareness, with a particularly central role for the Regulation of Aggressive Impulses, in line with previous findings (Martínez-Ferrer, Moreno, & Musitu, 2018). At a conceptual level, these four domains express more careful and considerate online behavior and were indeed associated with the ability to make considerate decisions to use mobile devices. This latter domain, which could be viewed as either not feeling a strong urge to go online or being able to control the urge, has

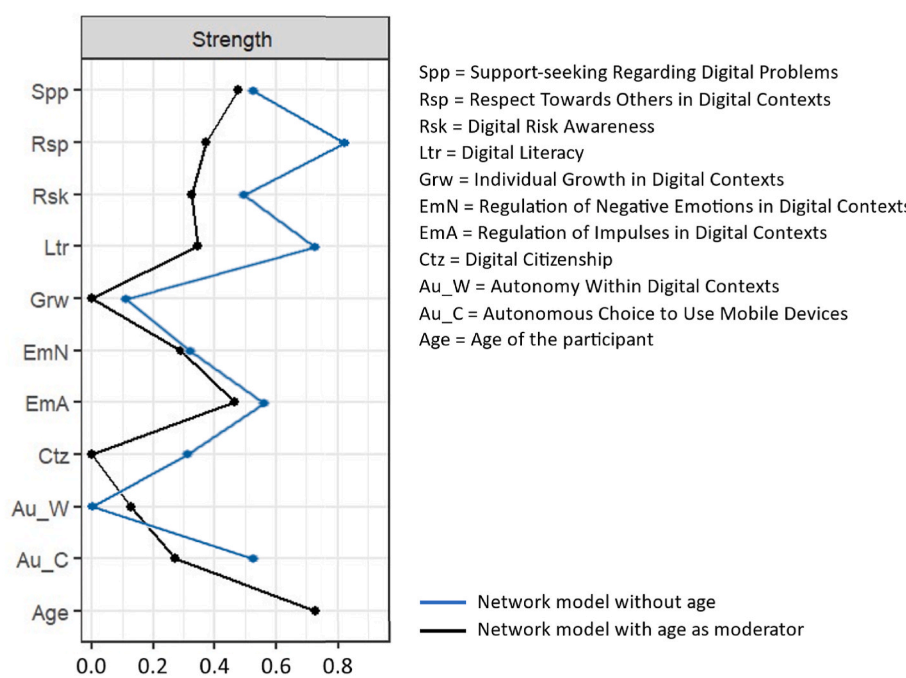

Fig. 4. Strength centrality scores for each domain of the Digital Maturity Inventory. Blue lines indicate strength scores for the model without age; black lines indicate strength scores for the model including age as a moderator variable.

frequently been researched in the context of problematic smartphone use. Recently, using network analysis, the loss of control was indeed demonstrated to be highly central to the network of problematic smartphone and social media use (Huang, Lai, Xue, Zhang, & Wang, 2021; Svicher, Fioravanti, & Casale, 2021). Correspondingly, it has been shown that individuals who more strongly experience a Fear of Missing Out (FoMO; see item 2 of the Autonomous Choice to Use Mobile Devices domain), are more likely to exhibit maladaptive emotional responses, including feeling angry or depressed, in response to failures or frustrations with digital technology (Hadlington & Scase, 2018). Within this second cluster, the strong connection between Risk Awareness and Respect towards Others was particularly salient. It is possible that individuals who are more aware of the (emotional) risks of for example antisocial conduct or cyberbullying, are also less likely to exhibit these behaviors themselves. Conversely, antisocial behavior such as insulting others can be viewed as risky behavior itself (Gámez-Guadix, Borrajo, & Almendros, 2016; Sasson & Mesch, 2014; Ybarra, Mitchell, Finkelhor, & Wolak, 2007), and being risk aware and careful might thus actually comprise behaving respectfully.

Interestingly, making thoughtful decisions about the specific content to engage in was rather unconnected within the network, suggesting that choosing the specific online activity is less decisive for digital maturity than choosing whether to go online in the first place. In the same vein, Individual Growth in Digital Contexts and Digital Citizenship, both related to using digital devices for growth and adjustment, either at the individual or societal level, are only weakly connected with the other domains, implying a less critical role within the network.

A striking conclusion that can be derived from our network analysis is that, although age mediated some relationships within the network, it did not moderate the interactions between DIMI variables. Even though the measure was developed specifically for adolescents, this suggests that the inherent structure of digital maturity is rather stable across ages ranging from late childhood into adulthood, signifying the robustness of the DIMI and its concept. Moreover, targeting certain domains for interventions would have comparable effects for all these age groups.

A more detailed comparison of our findings with the *a priori* conceptualization of the DIMI by Laaber and colleagues (Laaber, Florack, Koch, & Hubert, 2023) yields some interesting insights. Laaber initially considered three main capacities, each consisting of several domains. The two main subclusters identified here partially overlap with these three capacities, although they also differ on important points. Our first cluster pertaining to digital skills and problem solving largely agrees with Laaber's capacity to *master increasing digital challenges and solve problems*, which included Digital Literacy, Individual Growth, Risk Awareness and Support-seeking. Although here, Individual Growth was found to be only weakly connected to the other maturity domains, Digital Literacy and Support-seeking, and to a lesser degree Risk Awareness, were indeed interconnected. The current results suggest that the domains within Laaber's other two capacities might benefit from being merged. Specifically, we indeed observed high interconnectedness between the Regulation of Negative Emotions, the Regulation of Impulses and Respect towards Others, as was theorized for the capacity to *interact adequately with others and contribute to society*. Importantly, the fourth theorized domain within this capacity, Digital Citizenship, was found to be non-central to digital maturity. Instead, the Autonomous Choice to Use Mobile Devices, from Laaber's capacity to *use digital technologies in an autonomous and self-determined way*, seemed to cluster together more strongly with our second cluster. We therefore postulate that digital maturity can be subdivided into two main clusters, one relating to technical competences and one relating to careful use, with the former being more likely to be mediated by age.

Furthermore, the DIMI domains together form a weighted sum score of digital maturity. These weights were originally determined by experts in the field. Whereas these experts rated Digital Risk Awareness and Individual Growth as particularly pertinent for digital maturity, the network analysis reveals only a medium or even low centrality for these domains. Conversely, whereas our analysis showed high centrality strength for Support-seeking and the Regulation of Impulses, the experts-ratings only indicated low to medium importance of these domains. Agreement between the expert-ratings and our results can be found for Autonomy Within Digital Contexts and Digital Citizenship, which were both of low importance. The latter can be seen as a dimension that would ideally be displayed, but cannot be expected for everyone, and was indeed a domain on which participants scored relatively low. Although the experts had strong backgrounds in the field of digital technologies and child development, future large-scale studies might reveal the need for refinement or adjustments of these weights that more closely resemble the centrality scores found here. Nevertheless, a network approach would prescribe to view digital maturity as a configuration of domains and the causal relations between them (Bollen & Diamantopoulos, 2017; Borsboom, 2008; Cramer, Waldorp, van Der Maas, & Borsboom, 2010; Van Der Maas et al., 2006), which would preempt the need to calculate an overall sum score.

4.1. Limitations and future directions

Although our study provides important insights to advance our understanding of digital maturity, some important limitations should be taken into account. First, it is important to note that, although a network approach assumes that the concept of interest is formed by the causal relations between domains in the network, the connections revealed by this analysis are of a correlational nature. Cause and effect can thus not be determined. Therefore, rather than uncovering how the causal relationships run within the network structure, the current study served as a starting point to explore potentially important domains of digital maturity that can be targeted by interventions. Current studies suggest that intervention apps that target self-control to limit total time spent on smartphones or with specific social media or gaming apps are somewhat successful, at least on the short-term (Augner, Vlasak, Aichhorn, & Barth, 2022; Hiniker, Hong, Kohno, & Kientz, 2016). However, as digital devices and time spent online can also be beneficial, interventions that aim at promoting mature use rather than at merely limiting general use can be highly valuable. Our results show that Support-seeking and Regulation of Impulses were relatively central to the network, and changes in scores on these domains might therefore greatly impact many other domains. Interventions that involve parents, teachers or even peer groups are therefore promising avenues to increase digital maturity, particularly Digital Literacy and Risk Awareness, thereby aiding in the online safety of our young generation. Indeed, small-scale studies aiming at increasing adolescent-parental or peer-group communication have shown positive initial results on problematic smartphone and internet use (Ko et al., 2015, pp. 1235–1245; Liu et al., 2015). Furthermore, interventions for reducing aggressive impulse regulation, or reactive aggression, have shown to be promising in offline settings (Barker et al., 2010; Denson, 2015). They might therefore also positively affect antisocial online behavior and, indirectly, online risk awareness, as well as other regulatory processes, including the regulation of negative emotions in response to upsetting online experiences and self-control to resist the urge to go online too often. In contrast, Digital Citizenship was observed to be non-central to the digital maturity network. However, interest in youth online civic engagement is increasing (Chan & Guo, 2013; Jones & Mitchell, 2016; Jugert, Eckstein, Noack, Kuhn, & Benbow, 2013; Lee, Shah, & McLeod, 2013), and educating teens on how to use the online environment and social media for civic participation could prove fruitful.

Moreover, we tested a cross-sectional sample, which did not allow us to compute directional effects of age. Moreover, any effects of age, or lack thereof, could be due to potential cohort effects, especially given the nature of our research topic. Future longitudinal studies can more closely examine any (moderating) effects of age on different domains of digital maturity. If these studies would find no moderating effect of age either, this would strengthen the notion of digital maturity as a relatively stable, trait-like measure.

Although our sample size allowed us to estimate parameters with high precision, the expected sensitivity to detect both pairwise interactions and moderation effects was relatively small (Haslbeck et al., 2021). In other words, the probability that the parameters that were recovered were true parameters is high, but it is possible that we missed true parameters. Relatedly, our recruitment process was rather unselective and we do not have data on individual characteristics such as social economic status or ethnicity, making us unable to test if our samples are representative of the German or Dutch populations. More controlled recruitment procedures and larger-scale studies, with samples size of 600–1000, would substantially increase representativeness and the sensitivity of the network analyses used here, and would therefore be useful to establish the robustness of the current findings.

Our total sample was recruited in two different countries, with the 9–16 year olds being recruited in Berlin, Germany and the adult group being recruited in Amsterdam, the Netherlands. A follow-up analysis showed that the network structure of digital maturity was invariant to the substitution of the Dutch adult sample for the German adult sample, speaking to the robustness of our effects to different, although culturally and lexically very similar (Dyen, Kruskal, & Black, 2007; Halman, Reeskens, Sieben, & van Zundert, 2022; World Values Survey 7, 2023), samples. Future studies could utilize network analysis to assess whether any differences in network structure exist between more culturally diverse populations, which could inform more tailored interventions for different populations.

Finally, our sample included respondents between 9 and 43 years of age, all of whom received the same instrument that was developed for 12–18 year olds, meaning that some of the respondents fell outside the specific target group of the DIMI. However, the instrument was co-created with youth of different ages and developmental experts, and given that all of the questions are very general and high-level and that they can be understood by all ages, the DIMI was found to be appropriate for ages 9 and up. Some questions, mainly those pertaining to literacy and support-seeking, might have been less relevant for the older respondents. Although we do indeed see that older respondents score differently on these domains, the questions would most probably not be understood in a different way.

To make sure that these specific domains did not affect the rest of the network, i.e. the domains that relate to the careful use of digital devices, we conducted a control-analysis without these domains (not reported here), which confirmed that the cluster including Regulation of Negative Emotions and Aggressive Impulses, Respect towards Other, Risk Awareness and Autonomous Choice was not affected by the removal of these domains and can thus be interpreted equivalently for all age groups.

5. Conclusion

In sum, our network analysis revealed interesting insights into the interactions between digital maturity domains, with two main clusters emerging, which related to i) skills and problem solving and ii) careful and considerate online behavior, respectively. Importantly, the network structure did not depend on age, indicating its robustness across development. The current study exposes central roles for support-seeking and the regulation of aggressive impulses, thus generating valuable starting points for potential intervention measures to enhance overall maturity by influencing other, related domains.

CRediT authorship contribution statement

Lieke Hofmans: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Annemarijn van der Stappen:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Wouter van den Bos:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Wouter van den Bos reports financial support was provided by European Research Council. Wouter van den Bos reports financial support was provided by Horizon 2020 European Innovation Council Fast Track to Innovation. If there are other authors, they 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

The data and analysis scripts used in this article will be made publicly available before publication at osf.io/42bzw.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2024.108239.

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