Towards a Composite Index for Digital Maturity: An Unsupervised Machine Learning Approach

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TOWARDS A COMPOSITE INDEX FOR DIGITAL MATURITY: AN UNSUPERVISED MACHINE LEARNING APPROACH

Research full-length paper

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Abstract

In recent years, a considerable amount of research has explored the negative effects associated with the use of ICTs and linked it to several health issues that can pose consequences at the societal level as well as on an individual level. Despite the negative effects, the use of ICTs also provides a range of benefits and researchers are in particular interested in how we can help young people with obtaining a beneficial digital engagement with ICTs. Motivated by the advantages ICTs bring, a new concept named digital maturity has been proposed. Digital maturity is a multidimensional concept that consists of three capabilities. The first capability focuses on young people's ability to make autonomous choices about using mobile devices and exercising autonomy within digital contexts. The second capability involves digital literacy, individual growth in digital contexts, digital risk awareness, and support-seeking regarding digital problems. Finally, the third capability consists of the regulation of negative emotions and aggressive impulses in digital contexts, respect towards others in digital contexts, and digital citizenship for adequate interaction with others and contribution to society. To measure digital maturity based on these ten dimensions, a composite index (CI) named digital maturity inventory (DIMI) has been constructed. The DIMI can be used to gain an overview of the aggregated level of digital maturity in young people in a country or region by applying experts' opinions on how much weight each dimension should be given. The challenge that exists with using expert's proposed weights for the dimensions in a CI is that they not always are in line with their relative importance. In this paper, we examine the relative importance of the ten dimensions from a data-driven perspective using real-world data with an interest in optimizing the weights used to predict young peoples' digital maturity. Our result demonstrates a misfit between experts' opinions and the relative importance. Thus, based on our empirical evidence, we propose that an adjustment of the weights applied for the DIMI needs to take place.

Keywords: ICTs, Digital Maturity, Composite index, Children's Digital Maturity

1 Introduction

With the rapid growth of new information and communication technologies (ICTs), there has also been an increase in the number of opportunities and risks present in the digital environment. This has got both researchers and scholars attention from various disciplines. They are interested in obtaining a better understanding of young people's online behavior because they frequently use their mobile devices (Livingstone et al., 2018) and are heavily engaged in diverse digital activities (Eurostat, 2019). Among the benefits, ICTs have been found to facilitate communication, entertainment, and self-expression (Ólafsson et al., 2013). For instance, young people use their mobile devices as important lifestyle organizers to support their personal needs and social arrangements (Carroll et al., 2002). Despite these benefits, ICTs also give rise to several risks to young adults. Young adults, who struggle to control their use of social networking websites or gaming, may end up spending excessive amounts of time on their devices, neglecting other important activities. This can lead to accompanying risks, such as addiction, sleep disturbance, and decreased academic performance (Kuss and Griffiths 2012, van Deursen and van Dijk 2015, Hawi and Sudira 2019, Kwon et al. 2013). These risks are important issues that can pose several consequences for our society if they are not dealt with. A useful tool to help keeping an eye on the development and drag attention to important issues is the use of a composite index. A composite index (CI) can encompass a multifaceted construct that consists of several dimensions that each are measured by a range of indicators. By synthesizing the dimensions and indicators, it produces an output that can be used to understand the concept more clearly e.g., researchers, practitioners, and policymakers use them extensively for a range of areas because they have the potential to inform future interventions (OECD et al., 2008, Dobreva et al., 2021). A newly proposed CI for addressing young people's online behavior is the Digital Maturity Inventory (DIMI) that measures the underlying construct digital maturity (Laaber et al., 2023). Digital maturity is defined as the capabilities and attitudes needed in young people to address the challenges present in the digital environment. Through its dimensions, it assesses young people's self-determined as well as socially responsible use of digital technology and acknowledges that the use of digital technologies can either support or impede psychological growth and positive social adjustment. These online capabilities are unique and need to be developed in addition to their offline capabilities. Young people, who solely rely on capabilities developed for the offline world, may not be able to manage their online behavior effectively and reap the opportunities present within the digital environment. With the DIMI, researchers, practitioners, and politicians can gain a more comprehensive understanding of young people's digital maturity levels. To apply the CI, it requires human input for all dimensions that each is measured by a number of indicators. The average scores of the indicators for each dimension are then multiplied by weights (i.e., the importance score for each dimension), which have been determined by a group of experts before they are added together to obtain the final score for digital maturity. Currently, there has been no empirical check of the dimensions' weights using data-driven techniques. Data-driven techniques are not subject to bias and are based on an actual distribution from real-world data (Greco et al., 2019). To further advance the development of the DIMI, the main contribution of this study is to provide empirical evidence using real-world data for its composition of the theoretical dimensions using a data-driven approach that apply unsupervised machine learning to investigate the weight structure of the DIMI dimensions from a socio-technical perspective.

2 Theoretical Framework

2.1 Young People's Online Behavior

The literature on the use of ICTs by young people has predominantly focused on screen time and digital literacy and lacks a more interdisciplinary perspective (Chassiakos et al., 2016; Livingstone et al., 2018). Both screen time and digital literacy are important aspects as an excessive screen time can have negative effects on young peoples' health and well-being (Van Deursen & Van Dijk, 2015), and digital literacy is important for enabling young people to engage safely and effectively with ICTs (Livingstone et al., 2018). However, recent research has highlighted the need for a more comprehensive understanding of young people's use of mobile devices, which considers the broader social and cultural contexts of their digital engagement (Livingstone et al., 2018). To address this need, the concept of digital maturity has been proposed as a more holistic approach to understand young people's ICT-related activities (Labeer et al., 2023). Digital maturity encompasses a range of competencies beyond technical skills and screen time management and is defined as the ability of young people to assess and regulate their behavior when using ICTs in different contexts. Developing digital maturity helps young people to navigate in the complex digital environment and make informed choices about their digital engagement.

2.2 Digital Maturity

Digital maturity is a contemporary concept, measured as a second-order construct with ten formative first-order dimensions, which provides a more comprehensive understanding of young peoples' mobile ICT activities in today's society. According to Labeer et. al., (2023), digital maturity encompasses three fundamental capabilities that young people should develop to use ICTs in a self-determined and socially responsible way, managing the increasing digital challenges, and interact appropriately with others. The first capability includes the ability to make autonomous choices about using mobile devices and exercising autonomy within digital contexts. The second capability involves digital literacy, individual growth in digital contexts, digital risk awareness, and support-seeking regarding digital problems. Finally, the third capability consists of the regulation of negative emotions and impulses in digital contexts, respect towards others in digital contexts, and digital citizenship for adequate interaction with others and contribution to society. The names and the definitions of the dimensions are mentioned in Table 1. The items for the autonomy within digital context and autonomous choice to use mobile devices dimensions collectively measured impulsive behaviour. Autonomy within digital context assessed their ability to choose what they did while using digital devices, while autonomous choice to use mobile devices explored their autonomy in choosing to be online or not, including factors such as fear of missing out (FOMO). The items measuring digital literacy assessed their knowledge of privacy settings on social media sites, ability to disable website cookies and understanding of how to store files on the cloud. Individual growth in digital contexts was indicated by the extent to which they were learning new skills and useful information through their use of digital technologies. Digital risk awareness was assessed by asking them about their level of caution when using digital technologies and the importance they placed on their own safety while being online. The support-seeking regarding digital problems dimension measured the extent to which they sought help from parents, siblings, or friends when encountering technical or social problems online. The regulation of negative emotions in digital contexts dimension measured the extent to which they were affected by negative experiences online, such as becoming upset or annoyed, and how long it took them to recover from these experiences. The regulation of impulses in digital contexts dimension assessed their reactions to criticism or insults received online and whether they acted impulsively without considering the consequences or regretted their actions later. Respect towards others in digital contexts was assessed by considering their attitudes toward others, their ability to respect the opinions of others while online, and their use of appropriate language when disagreeing with others. Finally, the digital citizenship dimension was assessed through items that explored the extent to which they used technology to improve their local communities, support environmental campaigns, and stand up for important issues.

Dimension Name	Definition	Weight
Autonomous Choice to Use Mobile Devices	Using mobile devices out of one's own choice rather than a feeling of obligation or compulsion	0.10
Autonomy Within Digital Context	Deliberately choosing which digital contexts to engage with, viewing content which one finds interesting and enjoys	0.09
Digital Literacy	The technical skills to use mobile devices and the internet in a safe and effective manner	0.10
Individual Growth in Digital Contexts	The ability to use mobile devices and digital contexts for personal learning and growth	0.10

Digital Risk Awareness	Managing risks related to mobile devices and the online environment by being aware of potential dangers and influences	0.12
Support-seeking Regarding Digital Problems	The ability to seek support from others when encountering problems regarding mobile devices or digital contexts	0.10
Regulation of Negative Emotions in Digital Contexts	The ability to control one's behavior and reactions to negative experiences in digital contexts	0.10
Regulation of Impulses in Digital Contexts	The ability to control and effectively regulate negative emotions due to frustrations in digital contexts	0.09
Respect towards Others in Digital Contexts	Acting respectfully when engaging with others and in content one shares online	0.10
Digital Citizenship	Using mobile devices and digital contexts to contribute to society and support important causes	0.08

Table 1. Overview of the dimensions for assessing Digital Maturity

2.3 Composite Index for a Multidimensional Concept

A CI provides a way to gather and synthesize the dimensions of a multidimensional concept, which cannot be captured by a single variable, to inspect and gain a comprehensive overview of a given phenomenon (Zani et al., 2023). They can be useful for obtaining comparisons between countries or regions and, if they are updated regularly, provide an overview of the evolution of a given situation over time. Researchers, practitioners, and policymakers use CIs extensively for a range of areas as they have the potential to inform future interventions (OECD, 2008; Dobreva et al., 2021).

DIMI is the developed CI for the multidimensional concept, digital maturity, that can assess young people's use of their mobile devices. The higher score on the DIMI, the better the digital maturity level is for a group of young people in a specific country or region. To aggregate the dimensions of DIMI and reach the final score for the level of digital maturity, a group of experts was used to determine the weights for each dimension by means of the budget allocation process (BAP). BAP is a method where experts are asked to allocate a certain number of points to each dimension based on their experience and subjective judgment. Following this, the weights for each dimension are calculated as average budgets in a transparent, straightforward, and in a fast manner (OECD, 2008). In the case of DIMI, each dimension was rated on a 7-point Likert scale ranging from 1 = "totally unimportant" to 7 = "very important". The resulting ratings were used to determine the weights for which the mean rating for each dimension was divided by the sum of all mean ratings and then multiplied by 100. The group of experts to assess the ten digital maturity dimensions consisted of a diverse group of people in terms of discipline (e.g., psychology, computer science, neuroscience, sociology), seniority, and geographic origin. According to the experts, all the dimensions in DIMI were important, with mean scores ranging from 4.64 to 6.43. The dimension digital risk awareness from the second capacity was considered the most important dimension ($M = 6.43$, $SD = 0.65$), and digital citizenship from the third and last capacity was rated as the least important dimension ($M = 4.64$, $SD = 1.39$) (Labeer et. al., 2023). A rescaled version of the experts' opinions on the allocation of weights, which are country-independent, are provided in Table 1.

2.4 Socio-Technical Perspective

To understand how a CI such as the DIMI can be useful for our society and what purpose it should serve, we turn to the socio-technical perspective. The sociotechnical perspective is a concept that has gained prominence within the Information Systems (IS) field, as it seeks to reconcile the "technical" and "social" aspects of any given system. Sarker et al. (2019) have described the sociotechnical perspective as an axis of cohesion in IS, which emphasizes the importance of behavior in relation to ICTs. They contend that ICTs are human-created tools that serve a purpose defined, perceived, or felt by humans, and that the design of any system should aim to integrate the technical and social aspects in a balanced manner. The sociotechnical perspective aligns with the focus of this research, as it regards the technical and social components in relation to ICTs as equally important. It is not recommended to prioritize one over the other, but rather, to establish harmony between them, as the interplay between the two is crucial. This perspective posits that seeking a fit or harmony between the technical and social aspects of a digital engagement can result in better outcomes, both instrumentally, such as higher productivity, and humanistically, such as greater well-being (Wallace et al., 2004). The concept of digital maturity can be considered a socio-technical concept, as it encompasses both the technical component, such as digital literacy, and the societal perspective, such as digital citizenship. To achieve a "Joint Optimization" between these dimensions, it is important to identify the primary dimensions that differentiate young people who have achieved digital maturity from those who have not. This understanding can facilitate the optimization of the interplay between the social and technical elements of the socio-technical system and suggest important moderations for the CI from a data-driven perspective. Thus, our theoretical framework aims to determine the relative importance of each dimension in digital maturity in order to achieve a holistic understanding of this socio-technical phenomenon (Figure 1). Even though DIMI has been developed by researchers, the sociotechnical perspective underscores the significance of involving diverse stakeholders, such as parents, teachers, and policymakers, in supporting young people's digital maturity. This perspective acknowledges that changes in the technical elements, such as the design of digital technologies, can have profound impacts on the social elements, such as the behavior of young people. A collaborative approach is essential in addressing the challenges and opportunities associated with young people's use of digital technologies.

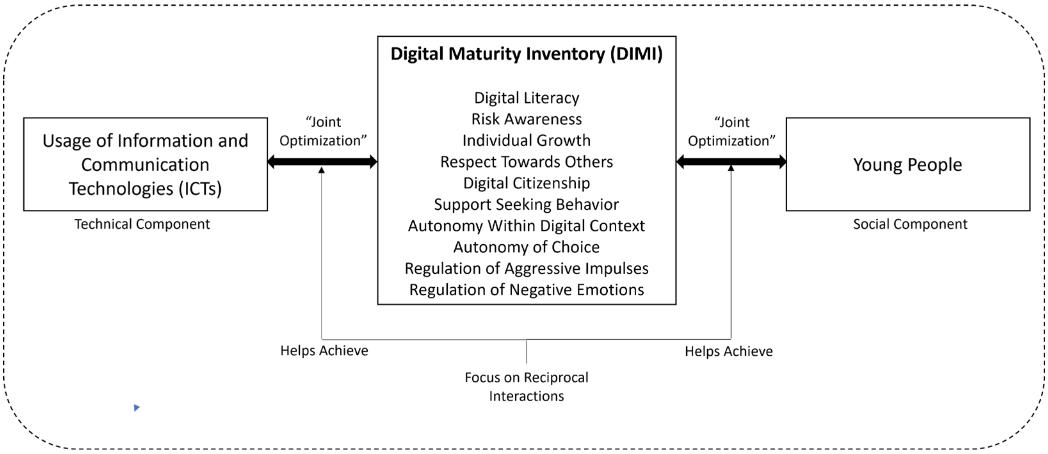

Figure 1. Theoretical Framework inspired by Sarker et. al., (2019)

The novelty of DIMI makes it crucial to ascertain its most significant dimensional aspects. It is imperative to determine how it is directing our attention towards individual factors, such as an autonomous and self-determined use of mobile devices, or the mastery of digital challenges and problem-solving, or if it primarily focuses on their ability to contribute to our society and engage in appropriate interactions with others in the digital world. Thus, in this paper, we propose an optimized allocation for the weight-structure to improve the DIMI and seek a harmony from a socio-technical perspective.

3 Methodology

This study focuses on examining the optimal interplay (i.e., weight structure) and finding the relative importance of the ten dimensions included in the DIMI. To determine the optimal interplay between the elements, one of three available methods is typically used; Equal weights, a subjective weighting method (e.g., Expert opinions via the BAP method), or an objective weighting method (e.g., Multivariate methods/statistical weighting techniques) (OECD, 2008; Maggino, 2017; Greco et al., 2019; Chen et al., 2022). The application of equal weights or the subjective weights are not without its challenges. The equal weight approach (i.e., all dimensions are allocated the same amount of importance) can lead to the potential pitfall that the dimensions in the CI implicitly are treated the same way. This is not deemed feasible as some dimensions may contribute more to the composite indicator than the remaining dimensions. For instance, in situations when an equal weighting scheme is chosen for indicators that are grouped into dimensions and then added together using equal weights, there is a risk of imposing an unbalanced structure on the CI (i.e., the dimensions consisting of more indicators will by default be allocated a higher weight). Another risk of using an equal weighting scheme is that it might lead to the unintended consequence that dimensions with a high degree of correlation are taking up a dominating part in the CI, which then results in increased attention to these dimensions when in fact this should have been adjusted for in one way or another. These risks are often encountered when there is an absence of an empirical foundation, insufficient knowledge, or a lack of consensus (OECD, 2008). In terms of subjective weights, there can be a risk of creating a CI that suffers from the bias introduced by researchers, and different variances and correlations among the variables might impact the chosen weights for the dimensions in an unintended manner (Becker et al., 2017). If a subjective weighting scheme (i.e., often determined by experts) shows approximately equal weights that then are aggregated into a final score, this approach can suffer from the same pitfalls as mentioned previously for the equal weights approach. Both approaches are compensatory in the sense that two very distinct observations can show the same level of digital maturity because scoring high on one dimension can offset a low score on another dimension. This is not a preferred property of the CI if the intention is that a young person with a medium score on all dimensions should be favored over a young person with a high score on half of the dimensions and a low score on the remaining dimensions. Because of these unintended properties of the equal weights approach and the subjective weights approach (i.e., expert ratings), the weights derived by both approaches are often referred to as nominal weights. Nominal weights should be distinguished from the relative importance of the dimensions as they do not represent the same thing (For a discussion on nominal weights versus variable importance see Paruolo (2013). In fact, it has been found that the nominal weights do not usually coincide with the importance of each variable (Paruolo, 2013; Becker et al., 2017). Therefore, Schlossarek et al. (2019) recommend that the variable importance is checked after the formation of the CI as the weight structure should reflect the empirical importance of the dimensions for the measured phenomenon of interest. In case, a high discrepancy exists between the nominal weights and the importance of the variables, an adjustment should be considered.

To provide empirical evidence on the weights for the dimensions included in the DIMI and overcome the aforementioned challenges, we have chosen to conduct a multivariate analysis. To carry out the multivariate analysis, several aggregation methods, such as principal components analysis (PCA) and data envelopment analysis (DEA) are available (OECD, 2008; Jiménez-Fernández & Ruiz-Martos, 2020). DEA is not a recommended approach because it focuses on maximizing the weights for each observation in a relative manner that prevent ranking and insights on performance in absolute terms (Jiménez-Fernández & Ruiz-Martos, 2020). Alternatively, PCA can be used as a multivariate approach to determine the most important dimensions as it permit ranking and does not produce weights that are dependent on the other observations. It allows one to identify a smaller number of factors (i.e., dimensions) that explain most of the observed variance. Even though it has previously been used for constructing a CI, one must be careful with applying PCA for formative measurement models as some important issues have been identified with using it for this type of measurement model (Mazziotta & Pereto, 2019). First, the derived weights depend on the covariance structure among the proposed dimensions. This is not aligned with a formative measurement model where the individual dimensions can have positive, negative, or zero correlations. The formative measurement model is not developed on the basis that the individual dimensions will correlate with each other. Secondly, the first factor is normally chosen to represent the weight-structure for the CI. When using the first factor based on the PCA results to construct the weight-structure, the CI consists of highly correlated dimensions that explains only a portion of the variance. This is not our interest because the formative measurement model precludes that we should avoid multicollinearity. Mazziotta & Pereto (2019) state that PCA is more suited for dimensionality reduction, which should be considered as a separate issue from the construction of CIs. In response to these issues, we have implemented a newly proposed unsupervised machine learning approach with fuzzy metrics for formative measurement models by Jiménez-Fernández et al. (2022) and fitted it to our context. The proposed methodology is unsupervised and takes an unlabelled dataset with the dimensions constituting the CI as input and determines the weights independent from other outcome variables (e.g., problematic mobile device use, addiction, etc.). In place of using other outcome variables, it constructs a surrogate outcome variable based on a combination of fuzzy metrics to guide the learning process. The fuzzy metrics are useful to establish "degree of truths" rather than using a "true" or "false" Boolean value. For instance, in our case, there is yet no well-defined boundaries for when we observe e.g., a low, medium, or high level of digital maturity. We cannot state in numerical values when it is possible to distinguish between these levels, nor can we determine exactly when a shift occurs from e.g., a medium to a high level of digital maturity. However, we do know that a high score on all dimensions should be pursued. The use of a fuzzy metric for each dimension in a CI can accommodate this by measuring a distance for each observation between each dimension and the associated reference vector. The reference vector for each dimension includes the highest obtainable value that an observation can score on a dimension. In this sense, we use the fuzzy metric proposed in the methodology to measure how far away each observation is from achieving the highest possible value for a given dimension. A flow chart of the methodology is shown in Figure 2.

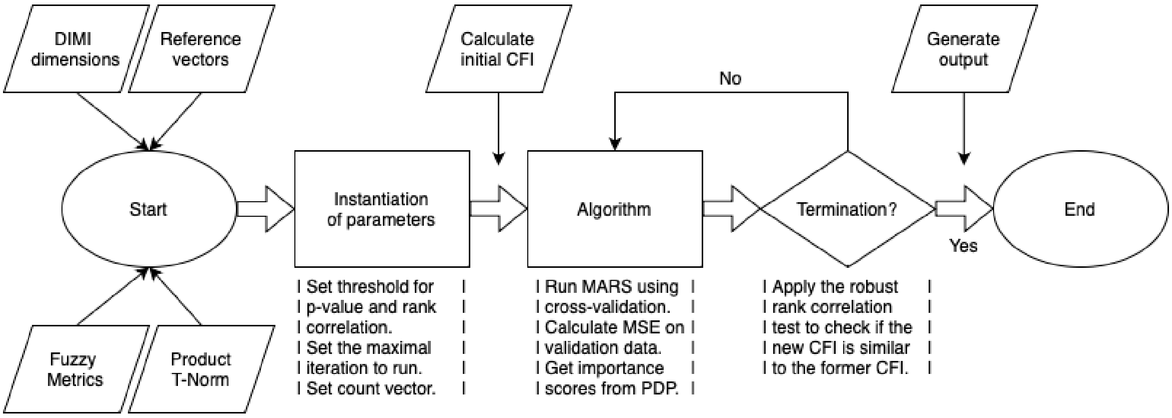

Figure 2. Flow chart over our adapted methodology by Jiménez-Fernández et al. (2022)

The starting values of our algorithm are important for its convergence to the optimal outcome. To outset the fuzzy metrics, equal importance scores is used for all dimensions. As all dimensions will be normalized, a value of one indicates that the highest possible value has been obtained for a given dimension, whereas a value between zero and less than one indicates a lower value for a given dimension. To obtain the final outcome variable, which will be referred to as the Composite Fuzzy Indicator (CFI) from now on, we combine the resulting distance value by using a t-norm that takes the product of all fuzzy metrics for each observation. In this manner, we can accommodate the complexity of combining several dimensions in a CI that is intended to reflect a multidimensional concept. The machine learning process is instantiated with the threshold for two control parameters. The first parameter is the threshold for the level of significance, which is set to 0.05 as often adopted within this field of research. The second parameter is the robust gamma rank correlation, which is a generalization of the traditional gamma rank correlation that tests if the ranking of the observations in one dataset is significantly similar to the ranking of observations in another dataset. Specifically, we test that the former CFI is similar to the new calculated CFI. The threshold for this parameter was set to 0.9, which is in line with what was applied by Jiménez-Fernández et al. (2022). In addition to these two control parameters, an arbitrarily large number of iterations as well as a count variable starting from 1 to keep track of the number of rounds the algorithm runs are set. Between the instantiation of the parameters and the algorithm, the first CFI is calculated as explained. When the first CFI is derived, the dataset with DIMI dimensions and the CFI value is split into a training set and a validation set. On the training data, the algorithm maps non-linear and stepwise relations between the proposed dimensions and the CFI by means of Multivariate Adaption Regression Splines (MARS) and 10-fold cross-validation. For the final MARS model, the mean squared error (MSE) is calculated and the first proposed weight structure is derived from partial dependence plots (PDPs). PDPs enable us to interpret the final estimated MARS model and calculate the variable importance of the dimensions with a standardized procedure. To determine if the final weight-structure for the dimensions has been achieved and the algorithm should be terminated, a robust rank correlation test between the initial CFI and the new CFI is performed. If they are independent, the weight-structure will replace the equal weights in the calculation of the initial CFI and the rest of the procedure is repeated several times until the CFI from the current iteration is not significantly different with the CFI from the previous iteration. When this happens, the algorithm stops and the output with the final weight-structure that represents the importance of the dimensions is obtained as a result.

4 Data

Drawing on insights from the field of psychology, Laaber et al. (2023) have identified digital maturity as a complex construct comprising of ten distinct dimensions. Through the use of latent variables and a formative measurement model, each dimension is represented by a single variable that reflects a range of indicators corresponding to specific behaviors exhibited by young people when using their mobile devices. The factorial structure for digital maturity has been validated using best practices, including confirmatory factor analysis to check for its internal consistency, construct reliability, and average variance extracted as well as discriminant and convergent associations with other relevant constructs, such as age, amount of mobile device use, and personality traits. To collect real-world data on digital maturity, Laaber et al. (2023) refer to a survey instrument for the DIMI comprising two parts. The first part of the survey has to be completed by young people's parents, while the second part including the ten dimensions has to be filled out by the young people themselves. In this paper, we use secondary data on young people's level of digital maturity that has been collected by means of a professional market agency to adolescents aged 12-18 years old in Austria and Germany in two waves. The survey consisted of 32 questions corresponding to the latent variables measuring the individual dimensions. Responses were collected on a 5-point Likert scale, where a score of 1 indicated "Never", a score of 2 indicated "Rarely", a score of 3 indicated "Sometimes", a score of 4 indicated "Often", and a score of 5 indicated "Always". All items for measuring the ten dimensions of digital maturity were within bounded scale points from 1 to 5 on a Likert scale, preventing the possibility for outliers to exist in the dataset. To ensure data quality, attention checks were used to detect inattentive responses among the respondents.

5 Results

Digital maturity has been proposed as a multidimensional concept that consists of three main capacities that address the digital challenges faced by young people when aiming for positive individual and social development in the digital environment. Each of these capacities consists of several dimensions that can be considered as single latent variables reflected by multiple indicators that represent young people's specific behaviours when using their digital devices. The socio-demographics for the collected data is shown in Table 2. The overall sample consists of 1890 respondents of which 946 were from Austria with a mean age of 14.4 (1.79) and 944 of the respondents were from Germany with a mean age of 14.3 (1.72). The samples for both countries had a close to equal distribution in terms of gender. This enabled the possibility to analyse the relative importance of the DIMI dimensions for each of the two countries.

	Austria	Germany
Number of respondents (%)	946 (50.05)	944 (49.95)
Age (SD)	14.4 (1.79)	14.3 (1.72)
Gender (Female/Male/Other) (%)	462 (48.8) / 482 (51.0) / 2 (0.2)	477 (50.5) / 464 (49.2) / 3 (0.3)

Table 2. Socio-demographics.

In Table 3, the mean values for the pooled sample as well as the Pearson correlation matrix for the ten dimensions are shown. The first capacity on how to use digital technologies in an autonomous and self-determined way shows mean values of 3.39 and 4.28 for young adults' autonomous choice to use their mobile devices and their autonomy within digital contexts, respectively. The second capacity on how to master increasing digital challenges and solve problems has mean values of 3.78 (Digital literacy), 3.53 (Individual growth in digital contexts), 3.86 (Digital risk awareness), and 3.63 (Support-seeking regarding digital problems). The last and third capacity addressing the young people's ability to interact adequately with others and ability to contribute to the society shows mean values of 3.62, 3.73, 4.07, and 2.36 for the dimensions: Regulation of negative emotions in digital contexts, regulation of impulses in digital contexts, respect towards others in digital contexts, and digital citizenship. Overall, this reveals that there is a tendency to score above average on most of the dimensions except for digital citizenship. The Pearson correlation matrix shows that none of the correlation coefficients were highly correlated and there were no problems in terms of multicollinearity. This is necessary as it otherwise could lead to a problem in our chosen estimation method (PDPs) that relies on the assumption with independent dimensions. Moderated correlations were found between regulation of impulses in digital contexts and regulation of negative emotions in digital contexts as well as between respect towards others in digital contexts and digital risk awareness. The remaining correlations were considered as low or little, if any, correlations between the dimensions. This highlights that PCA would have been a problematic method for determining the weights as it is unlikely that all dimensions share one common factor, and the resulting weight-structure would then not be able to capture as much of the variation in the data as wished.

Dimension	M (SD)	1	2	3	4	5	6	7	8	9	10
Autonomous Choice to Use Mobile Devices	3.39 (0.94)	1.00									
Autonomy within Digital Contexts	4.28 (0.64)	0.04	1.00								
Digital Literacy	3.78 (0.98)	-0.01	0.23	1.00							
Individual Growth in Digital Contexts	3.53 (0.69)	-0.08	0.18	0.25	1.00						
Digital Risk Awareness	3.86 (0.83)	0.25	0.18	0.26	0.23	1.00					
Support-seeking Regarding Digital Problems	3.63 (0.82)	0.08	0.12	0.04	0.22	0.31	1.00				
Regulation of Negative Emotions in Digital Contexts	3.62 (0.88)	0.40	0.12	0.12	-0.03	0.17	0.05	1.00			
Regulation of Impulses in Digital Contexts	3.73 (0.86)	0.45	0.08	0.10	0.02	0.30	0.11	0.49	1.00		
Respect towards Others in Digital Contexts	4.07 (0.73)	0.24	0.29	0.23	0.22	0.52	0.32	0.20	0.39	1.00	
Digital Citizenship	2.36 (0.95)	-0.18	-0.10	0.20	0.29	0.17	0.06	-0.15	0.16	0.10	1.00

Table 3. Means, SDs, and Pearson correlation matrix for the variables.

The estimated variable importance plot for each country is shown in Figure 3. For both Austria and Germany, the variable importance plot suggests that some of the dimensions are more influential and dominating than the other dimensions. The most influential dimension in Austria was found to be digital citizenship. This dimension was followed by the dimension individual growth in digital contexts, and with the dimension regulation of impulses in digital contexts as the third most influential dimension. The top-three influential dimensions were almost similar for the German sample. However, with regulation of impulses in digital contexts as the second most influential and individual growth in digital contexts as the third most influential dimension. A remark here is that these three dimensions represent two out of the three capabilities. Digital citizenship and regulation of impulses in digital contexts represent young people’s capacity to interact adequately with others and contribute to society. Individual growth in digital contexts represents young adults' capacity to master increasing digital challenges and solve problems. The remaining dimension that represents young people’s capacity to use digital technologies in an autonomous and self-determined way is influential in Austria with both dimensions. In

Germany, this was not the case. Autonomous Choice to Use Mobile Devices has an impact, but the Autonomy Within Digital Context did not show an important role in contributing to digital maturity.

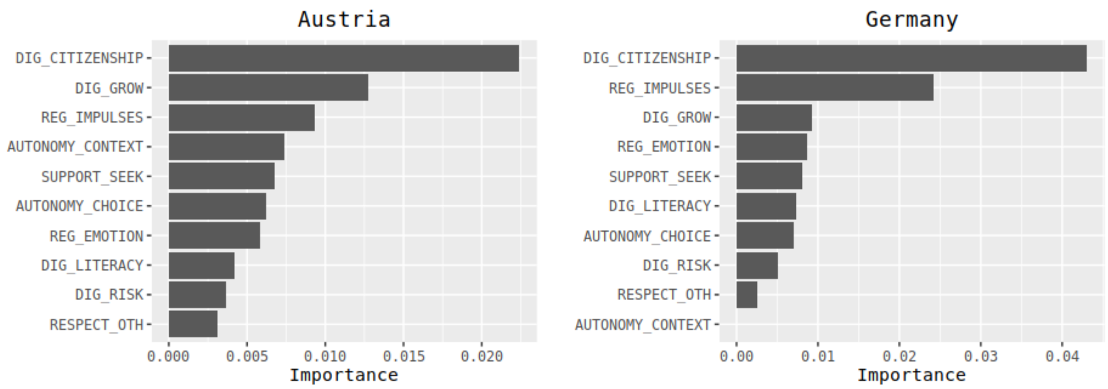

Figure 3. Variable Importance Plot

The data-driven weight structure for each country is shown in Table 4. The main deviation between the two countries in their respective weight structures was young peoples' autonomy within digital contexts. For Austria, this dimension has a high impact whereas in Germany it does not contribute to predicting digital maturity. Three of the other dimensions deviated in the magnitude of their relative importance for the dimensions. These were regulation of impulses in digital contexts, individual growth in digital Contexts, and digital citizenship. On the remaining dimensions, we only see very small differences. Overall, at a higher level, these data-driven weights for each of the three capacities provide an inclination towards non-equal weights for the ten dimensions constituting digital maturity. Thus, based on the new proposed weight-structure for Austria and Germany, respectively, there exists a discrepancy between the proposed nominal weights suggested by experts and the resulting data-driven weights.

Dimension Name	Austria	Germany	Expert-weights
Autonomous Choice to Use Mobile Devices	0.08	0.06	0.10
Autonomy within Digital Contexts	0.09	0.00	0.09
Digital Literacy	0.05	0.06	0.10
Individual Growth in Digital Contexts	0.16	0.08	0.10
Digital Risk Awareness	0.05	0.04	0.12
Support-seeking Regarding Digital Problems	0.08	0.07	0.10
Regulation of Negative Emotions in Digital Contexts	0.07	0.07	0.10
Regulation of Impulses in Digital Contexts	0.11	0.21	0.09
Respect towards Others in Digital Contexts	0.04	0.02	0.10
Digital Citizenship	0.27	0.37	0.08

Table 4. Data-driven weight-structure for the ten dimensions

6 Discussion

This paper contributes to the literature on young people's use of ICTs. ICTs are known to come along with both new opportunities and risks that have caused concerns among many scholars. The socio-technical perspective posits that we should aim for an alignment between the social and technical elements to achieve effective outcomes (e.g., quality of life or well-being) in young people. In this case, the use of ICTs represents the technical element, such as mobile devices, whereas the way young people use these technologies represents the social element. The interplay between these two elements can be optimized by using DIMI to assess what areas need more focus in the future to obtain a harmony. Yet, the novelty of both the phenomenon and DIMI still lack empirical investigation of how the ten dimensions of DIMI contribute to digital maturity. From the human perspective, scholars have identified theoretically relevant dimensions, and a group of experts have provided their opinions on how the DIMI should be composed into a useful CI. Their parameterization serves as a useful instantiation of the DIMI where all dimensions from their perspectives were confirmed to be relevant. Despite this confirmation from the experts, it can be derived that there is a discrepancy between the weights provided by the experts and the weights derived by a merely data-driven approach. From our inspection of the available data, the relationships between the dimensions and digital maturity were shown to be much more complex than suggested by the experts' allocation of weights. Hence, we propose that there is a need for an optimized allocation for the weight structure that can improve the DIMI by seeking the proposed harmony from a socio-technical perspective. There might be multiple reasons for this discrepancy. For instance, it might arise from the fact that digital maturity is a multi-dimensional construct. When experts give their opinions on the weight-structure, the number of dimensions can create decision fatigue due to the number of dimensions. Even though ten dimensions are within the recommended range of a maximum of twelve (OECD, 2008), it is not a simple task to be able to allocate the right importance to the dimensions when no prior data exists, or the phenomena is rather new as is the case with digital maturity. As raised in Greco et al. (2019), if the constructed index includes many dimensions, it can be hard to reach a consensus about their importance. Moreover, human bias is difficult to avoid in subjective methods. It is not precluded that the expert's opinions can be heavily influenced by their countries' priorities. In situations, when the expert group consists of experts from different countries, it can impact the weights as these might have different perspectives on what matters the most. If the weights, which have been even out due to multiple perspectives, do not adjust for correlations among the dimensions or take the non-linear relations with digital maturity into account, it can lead to unintended consequences (i.e., some dimensions are rated higher compared to others because the correlation between them enhances the importance). The limitation of applying experts from different countries, who all contribute with their opinions of the allocation of the weights for the dimensions, is that their different perspectives on the dimensions can lead to average weights because their disagreements even out. However, we do acknowledge that experts' opinions are especially valuable when there is a well-defined basis for a national policy (OECD, 2008). These reasons for the potential discrepancy have been addressed previously in the literature on how to construct CIs as the difference between nominal weights and the relative importance of the dimensions included in a CI. Another possible explanation for the discrepancy might be that the relative importance of the dimensions is sensitive to the applied data. The available data applied within this paper were based on two European countries. The insights into how the dimensions behave both within other European countries as well as outside the EU might be different. For instance, India is a developing country with an increased focus on digital literacy, which is evident from the fact that the Indian government's Digital India initiative aims to provide their citizens with access to digital infrastructure and services (Girdonia, 2023). Here, we might suspect that our results would have been very different in the main variabilities and the interplay between the dimensions would pose a different pattern. In situation like with digital maturity where there still does not exist a plethora of data, we propose that the applied data-driven methodology is modified to accommodate priors expressing what the experts know on a given subject. In this manner, the available subjective knowledge from experts is not neglected but rather incorporated in the applied methodology as priors to guide the search process for an optimal weight structure. This is in line with Chen et al. (2022), who argue that when both sources of information are available, it is recommended to combine the subjective information with the objective information to make the construction of the CI more accurate and reduce biases introduced by either source of information. Overall, our results contribute to the further establishment of the DIMI as a tool that can be used to measure young peoples' digital maturity useful for researchers, practitioners, and policymakers. DIMI has, in this paper, been formulated as a tool rooted in the socio-technical perspective, which enables us to provide it with a direction that is useful for obtaining insights into young people's level of digital maturity. The continued development of the DIMI is important to be able to provide a useful tool that can be used for real-world scenarios and future potential interventions to combat the many online risks that exists on the digital environment and help young people with obtaining a beneficial use of ICTs. Our work has theoretical implications. We provide evidence of the theoretical individual dimensions' influence on digital maturity. The exact focus of these dimensions should still be debated as they will be the dimensions, we use in the society for assessing young people's level of digital maturity in a given country or region. In terms of practical implications, our insights provide useful for practitioners and politicians, who discuss how to combat the impact that ICTs have on our younger generations. Based on these implications, our work provides some interesting directions for future research avenues. One possible and interesting research avenue is the use of design science to establish an application that can be applied by stakeholders for institutions, schools, or other decision-making purposes.

7 Conclusion & Future Work

There is growing evidence of ICTs impact on young people, but the research in relation to how we can mitigate a potentially problematic behaviour and foster a beneficial use is still in its infancy. An emerging and promising construct is digital maturity that comprises of a range of important competencies for young people to develop. For examining digital maturity, the DIMI has been proposed as a valuable tool that can be used to assess the various aspects and competencies of digital maturity in young adults that then can be used to initiate either preventive or supportive initiatives. From a socio-technical perspective, the goal of the DIMI is to seek a harmony between young people's use of ICTs (i.e., the technical element), such as mobile devices, and the way they use these technologies (i.e., the social element). The DIMI has been developed using expert-rated weights for obtaining a finalized score for digital maturity. In this paper, we challenge these expert-rated weights and present empirical evidence on how to compose the multi-faceted construct into an overall digital maturity score using unsupervised machine learning. The final selection of weights plays an important role as they influence the overall index score. In the results, we identified a discrepancy between the expert-based weights and the identified data-driven weights. Hence, we argue that an adjustment needs to take place. We found that country-dependent weights might be a possible solution because the derived pattern for the two countries differed with respect to the relative importance of the ten dimensions. In both countries, the resulting weight structures highlighted that some dimensions are more dominating than other dimensions. The main deviation between the two countries in their respective weight structures was found to be in terms of young peoples' autonomy within digital contexts. For Austria, this dimension has a high impact whereas in Germany it does not contribute to predicting digital maturity. Three of the other dimensions deviated in the magnitude of their relative importance for the dimensions. These were regulation of impulses in digital contexts, individual growth in digital contexts, and digital citizenship. Whether this is a result of different policies within the countries is up for further examination as well as it is up to researchers and practitioners to discuss whether a consensus about the dimensional weights should be reached across countries. As with any paper, our results are subject to some limitations. The first limitation is the self-reported data. The responses of the young people are their perceptions, which can be influenced by a social desirability bias. Another limitation is the choice of only two similar European countries. This impact our ability to generalize our obtained insights. Differences might be prevalent with other countries, but the same methodology will be useful to apply. A further research recommendation is therefore to examine the weight structure of other countries. To further improve this paper, we plan to extend our work on the CI for digital maturity in several ways. First, we want to examine the results of a hybrid approach that combines the experts' views on the relevance of the dimensions with the data-driven weights. The applied methodology used in this paper can be extended to incorporate both types of information as the set-up of the fuzzy metrics to construct the initial CFI currently relies on equal weights as a starting point. These equal weights can be replaced by the expert's weights. Secondly, we wish to challenge the assumption of having the same weights for all countries. This is wanted when the CI has to be used for an international comparison but not necessarily wanted from a national perspective. Most methods for obtaining the relative importance of the dimensions provide only one set of weights that can be used across countries. Extending the framework applied in this paper with an additional layer that can produce country-dependent specialized versions of the weight structure might serve as useful to provide further insights on a country's national priorities. This would make the applied framework in this paper more nationally oriented while still being able to provide the weights useful for an international comparison. Moreover, our current work will be enriched with a prescriptive section to inform future actions and recommendations on where to go from here.

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