How Life Transitions Influence People's Use of the Internet: A Clustering Approach

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Abstract. This research aimed, firstly, to define a conceptual model that considers potential resources/challenges (Physical, Cognitive, Emotional, Social, Material, Environmental, Digital) and describes how those influence the Internet use and modify human behavior during life transitions (e.g., changing school, finding a job). Secondly, starting on that model, user profiles were outlined. Instead of grouping study participants into pre-defined groups, clustering techniques were used to group users with similar profiles. The main advantage of this methodological approach is that the participant groups, i.e., different user profiles, emerged intrinsically from the data. A cross-sectional study was proposed based on the compilation of an Online questionnaire. The sample consists of 1.524 participants. Three clusters emerged with different mean ages: young adult users (mean age = 33.83), youngest users (25.79), and oldest users (36.80). Differences were identified between all dimensions measured, particularly between youngest users and oldest users.

Keywords: Life transition · Internet use · Clustering

1 Introduction

Integration between being online and offline is an important part of the psychology of human beings [15,44]. While, in some cases, it is possible to find a balance between these two aspects, in others integration might be problematic [27]. Accordingly, the theoretical perspective adopted for this research assumes that the Internet can become either a problematic or a functional tool depending on how it is used and the reasons behind that use [6,34,35]. Indeed, this research is underpinned by a theoretical framework that simultaneously considers both the positive and negative outcomes generated by the use of Internet. Ekbia and Nardi explained that Internet technologies could enable situations

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of inverse instrumentality, a process involving the objectification of users [16], whereby their behavior is regulated in a predictable manner, drawing them in or pushing them away from their activities. On the other hand, studies by Leont'ev [28] and later Kaptelinin and Nardi [24] proposed the construct of functional organ to describe how a tool (e.g., the Internet) allows people to achieve better and more powerful results which would not be attainable individually without that tool. Therefore, the goals of this research are firstly to define an integrative and flexible conceptual model that describes how life transitions (e.g., changing school, finding a job, moving to another city, etc.) linked to specific life periods influence people's use of the Internet (both in problematic and functional ways). Secondly, the model is adopted as a starting point for outlining user profiles that describe different ways of using the Internet and its applications. Furthermore, differences between these profiles are explored in terms of life transitions and challenges linked to these transitions. The benefit of this research is a proposed developmental model that connects user profiles to specific life periods characterized by transitions that generate challenges. Thus, the focus is not on the life stages themselves, as is the case in previous research about the use of the Internet by specific age groups (adolescents, emerging adults, adults, etc.), but rather on the transitions that people face, and on whether and how Internet use might facilitate these transitions.

Internet Use and Life Transitions: A Theoretical Perspective
Human development is characterized by transition and transformation processes in which chronological age is a dominant force (age always increases over time). In their *Lifespan Model of Developmental Challenge*, Hendry and Kloep [21] address the transitions and transformations arising from potential resources and challenges [26].

Potential resources characterize each individual from the beginning of their life. However, the distribution of those resources amongst individuals is uneven. Furthermore, there are some resources that seem "personal" to the individual (such as money) and others that are more socially defined (such as access to the education system). Thus, different micro- and macro-systems, with their different climates, laws, health systems, etc., generate different opportunities [9], such as access to education employment. From this perspective, resources and challenges are interdependent: [...] *challenges are defined by resources, and vice versa. Only by knowing an individual's resources can we decide whether a particular task is a challenge, and only by knowing a particular task can we decide if an individual has the resources to deal with it.* [...] [26]. Starting from these perspectives, it is also essential to consider the potential *digital* resources/challenges within the system (Fig. 1), since in recent years the use of the Internet has grown exponentially in every context of human life affecting relevant behaviors, interactions, and communications [2]. This is particularly true for the young, for whom technological literacy is crucial for interacting, finding information, work, recreation, and for a wide variety of other activities [5,43,47]. Figure 1 is a revised and extended version of Kloep, Hendry and Saunders diagram [26], that adds the transition processes to the interdependence of potential challenges and potential resources.

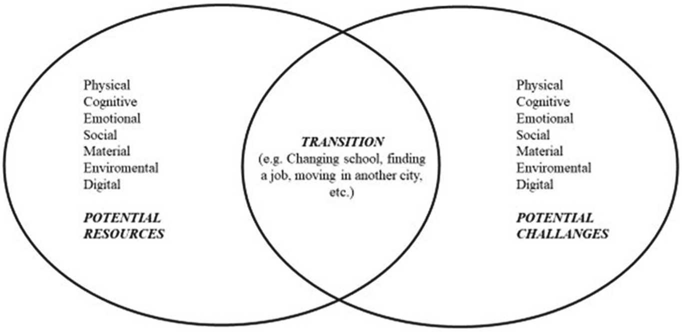

Fig. 1. Potential (digital) challenges and resources diagram, with transition as an intersection process.

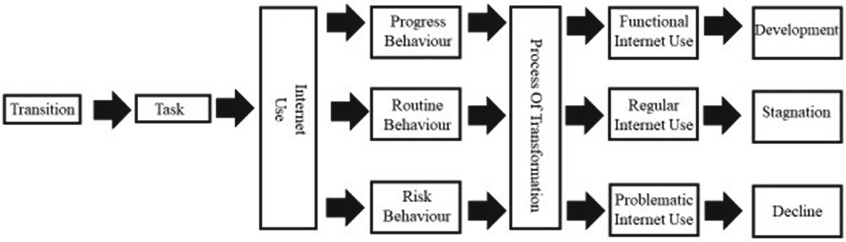

Fig. 2. Transition and transformation of internet use model.

The interdependence between potential resources and potential challenges inevitably affects the way in which the transition process takes place, develops and progresses. The Internet plays an important role in these evolutionary dynamics. Thus, it is pointless to speak of functional and/or problematic Internet use if we do not consider an evolutionary point of view regarding human transitions (Fig. 2).

Emerging Adults [3,4] namely people between 18 to 29 years of age, face a critical period of life in terms of human transitions [19], like shifting location for study or work purposes. These challenges involve many types of tasks, such as finding accommodation. To carry out these tasks quickly and easily, digital environments have become fundamental and irreplaceable. Nevertheless, in line with Hendry and Kloep's model [21,22], facing challenges not always leads to development. Thus, the use that young people make of the Internet could lead to three different kinds of behaviors: (1) Progress; (2) Routine or (3) Risk (see Fig. 2). So, according to these different kinds of behavior, Internet use could become: (1) functional, and thereby leading a person to overcome the transition and consequently bring about a development; (2) regular, leading a person to stagnation; (3) problematic, leading a person to a decline.

Summarizing, this is a person-centered model that offers an integrative and flexible perspective that includes potential digital resources/challenges and Internet usage, both in problematic and functional ways.

The Research Study

Previous research has already established that use of the Internet can be very helpful (functional) for facing transitions [17,36] but can also prove useless or even harmful (dysfunctional), decreasing the potential to face transitions [34]. Thus, the present study sets out to analyze the two poles of this continuum of functional-dysfunctional Internet use by using two specific concept/dimensions: Functional Internet Use (FIU) for the functional side and Problematic Internet Use (PIU) for the dysfunctional one.

Furthermore, previous studies have already found that functional or dysfunctional Internet use is determined by many factors, such as Self-Esteem, Self-Control, Online Social Support, Offline Social Support, Mindfulness, Cognitive Absorption, Life Satisfaction and Job Satisfaction [7,34]. Moreover, following the above assumption and the *Transition and Transformation of Internet Use Model* (Fig. 2), this study has sought to answer the following Research Questions: (RQ1) *Can transitions play a role in defining how and why people use digital technologies in different ways?* And since certain periods of life are associated with specific transitions and professional needs, (RQ2) *can the period of life determine different profiles based on digital technology use?*

Internet Use Habits: Devices, Social Networking Sites and Web Applications

Considering the environments people use to connect is crucial in order to gain a better understanding of the dynamics underlying Internet use during life transitions. In this regard, Social Networking Sites (SNSs) play an important role. During the transition from school to university or from school/university to work, the online contacts in a person's SNS networks could help them bridge gaps between their background knowledge and skills and those required in the new context in which that person will operate [18,36]. Particularly, the use of SNSs and Web Applications could often help people to cope with transitions because they represent a fundamental sort of pre-socialization with the new social context (e.g., that in which people move to attend university or join a new organization) by helping to create contacts with those who are already part of that environment. In this regard, it was expected that: (H1). Individuals' life periods that are specifically characterized by transitions and the attendant challenges posed influence how much they use the Internet, the devices they use to navigate it, and the applications they use.

Problematic Internet Use

This study adopts the concept of Problematic Internet Use (PIU) as used by Caplan [11,12], i.e. the individuals' predisposition to develop maladaptive Internet-related cognitive traits: (1) preference for online social interactions (POSI), (2) deficient mood regulation, (3) deficient self-regulation (compulsive use subscale and cognitive preoccupation subscale), (4) and negative outcomes. Factors considered in this study related to PIU are:

1. Self-Esteem: individuals with lower self-esteem are more prone to develop PIU symptoms [13];
2. Self-Control: people with low self-control might be led to PIU behavior [12];
3. Online Social Support and Offline Social Support: people with low offline social support tend to look for contacts online and consequently spend excessive time online [48];
4. Mindfulness: defines the presence or absence of attention related to what happens in the present [46]. It is possible to assume that this factor, combined with self-regulation, affects PIU because one of the most common experiences during time spent online is unawareness of time passing [30];
5. Cognitive Absorption: a high level of cognitive absorption when using the Internet allows better use of it (Heightened Enjoyment, Control and Curiosity) but, at the same time, it can lead to compulsive phenomena (Temporal Dissociation and Focused Immersion) [1].

Internet use during life transitions (e.g., from adolescence to emerging adulthood) could be dysfunctional because it is driven by exploration, challenges and changes [21]. In these periods, people are in the phase of selecting life prospects [4,21] and they tend to have different experiences, even in online environments, that may occur in a dysfunctional way, e.g. individuals characterized by low extroversion and low self-esteem are perceived as less popular both online and offline (hypothesis of social compensation) [49]. Thus, if individuals do not receive appropriate social support in daily life, they tend to create a parallel life to activate contacts and build relationships online in order to compensate for this shortage, and this could lead to a dysfunctional use of the Internet [49].

In this regard, considering the above assumptions, it was expected that: (H2). Dysfunctional use of the Internet could change during the individual's lifetime in response to challenges linked to their life transitions.

Functional Internet Use

Recent research has shown how the use of SNSs could lead to higher levels of well-being, possibly leading people to Functional Internet Use (FIU). Valkenburg, Peter and Schouten have highlighted how the frequency of use of SNSs indirectly affected Self-Esteem and psychological well-being in a sample of adolescents [45]. This frequency of use is affected by the frequency of positive feedback (e.g. "Likes" on Facebook or "Re-tweets" on Twitter) the sample received on their SNSs profiles. Moreover, in another study, analyzing the relationship between social capital (i.e. the potential benefits of creating and maintaining interpersonal relationships), Self-Esteem and the use of SNSs in American college students (and also in Italian students - see [36], it turned out that those with low Self-Esteem are more driven to use Facebook to maintain social capital than those with higher Self-Esteem [41]. In this regard during the transition from school to university or from school/university to work, for example, Social-Support and the use of SNSs play an important role. During these transitions, people using SNSs face a gap between the knowledge and skills they bring to the new organization and those required to work/study there. Thus, considering these assumptions, functional use of the Internet (FIU), namely use that facilitates completion of a challenge/task during a life transition, involves a number of factors: Self-Esteem, Online Social-Support, Number of Online Contacts (total sum of the contacts, including acquaintances and friends, that a person has on his/her social network/s profile/s), Life Satisfaction, and Job Satisfaction. It is expected that: (H3). Functional use of the Internet could change during life, in accordance with challenges linked to life transitions.

2 Materials and Methods

2.1 Data Collection

To verify the above hypotheses, a cross-sectional study was proposed based on the compilation of an anonymous online questionnaire [40], following approval from the local university bioethics committee. Respondents were recruited through announcements made on the main SNSs in Italy; efforts were made to achieve a gender-balanced sample population.

2.2 Sample Description

The sample consists of 1,524 participants, 1,050 female (68.9%) and 474 males (31.1%), with a mean age of 31.3 years (SD = 11.8).

2.3 Measures

The questionnaire items are grouped according to the three main areas analyzed in this research study, namely: (1) Measures of Problematic Internet Use, (2) Measures of Functional Internet Use, (3) Measures of Internet Use Habits.

2.4 Measures of Problematic Internet Use

Problematic Internet Use (PIU)
In order to measure PIU, the Italian version of Caplan's [12] Generalized Problematic Internet Use Scale 2 (GPIU2) was used. This consists of 15 items, measured on an 8-point Likert scale (1 = "definitely disagree" and 8 = "definitely agree"), in response to the instruction: "Indicate your degree of agreement-disagreement with the following statements". Cronbach's alpha for this scale was .92.

Self-Esteem
For this measure, the validated Italian version [38] of the Rosenberg Self-Esteem Scale was used [39]. It comprises 10 items on a 4-point Likert scale (1 = "strongly agree" to 4 = "strongly disagree"). Cronbach's alpha for this scale was .81.

Self-Control
Thirteen items from the Brief Self-Control Scale edited by Tangney, Baumeister and Boone [42], and later re-validated by Maloney, Grawitch, and Barber [33], were used. The selected items are those most predictive for Self-Control and are based on a 5-point Likert scale (1 = "not at all", 5 = "very much"). Cronbach's alpha for this scale was .83.

Online and Offline Social-Support
The Offline Social-Support Scale [48], which in turn was adapted from a previous study by Leung and Lee [29], was used. Cronbach's alpha for this scale was .93. Online Social-Support was also evaluated using the Online Social-Support Scale [48], indicating support from the online environment. For the 11 items covered in both scales, participants rated their agreement to the general statement "*How often is each of the following kinds of support available to you if you need it?*" according to a Likert scale from 1 = "never" to 5 = "all the time". Cronbach's alpha for this scale was .98.

Mindfulness
For this aspect, the Mindfulness Attention Awareness Scale (MAAS) was chosen [10,30]. This consists of a mono-dimensional score, with 15 items measured on a 6-point Likert scale from 1 = "almost always" to 6 = "almost never". Cronbach's alpha for this scale was .78.

Cognitive Absorption
The Cognitive Absorption Scale [1] was used as a measure of Internet engagement. The authors define the construct as " [...] *a state of deep involvement with software* [...]" [1]. The scale comprises 20 items measured on a 7-point Likert scale from 1 = "strongly disagree" to 7 = "strongly agree". Cronbach's alpha for this scale was .82.

2.5 Measures of Functional Internet Use

Functional Internet Use (FIU)
A brief scale for measuring FIU was specifically created for the purposes of this study. The scale is composed of 4 items: (1) "*being connected increases my ability to reach certain goals*", (2) "*being connected improves my productivity*", (3) "*being connected is useful for carrying out my activities*", (4) "*being connected improves my performance*". FIU was measured on a 7-point Likert scale, from 1 = "strongly disagree" to 7 = "strongly agree". Cronbach's alpha for this scale was .90.

Online Social-Support
As described earlier, Online Social-Support was evaluated using the Online Social-Support Scale [48].

Number of Online Contacts
The number of online contacts refers to: (1) contacts (i.e., all those individual subjects have on your online profiles); (2) acquaintances (i.e., those the subject

does not interact with regularly, whether online or in everyday life); and (3) friends (i.e., those with whom the subject habitually interacts, beyond simple online or offline contact in everyday life). Different thresholds were set for each of the three categories: 20,000 for online contacts, 10,000 for acquaintances, and 2,000 for friends. For the combined Online Contacts measure (total of all three categories), a threshold of 20,000 was set.

Life Satisfaction
This study adopted the Satisfaction with Life Scale [14], consisting of 5 items (5-point Likert scale from 1 = "strongly disagree" to 5 = "strongly agree"). All five are framed in a positive way (e.g., "*In general my life is close to my ideal*"). Cronbach's alpha for this scale was .87.

Job Satisfaction
Job satisfaction was measured using the Brayfield and Rothe job satisfaction scale [8], revalidated by Judge, Locke, Durham and Kluger [23]. This has five items ranked on a 10-point Likert scale ranging from 1 = "strongly disagree", to 10 = "strongly agree". As one of the aims of the study was to collect data from students as well, the scale's items included both job and academic satisfaction (e.g., "*I feel quite happy with my job/my studies*"). Cronbach's alpha for this scale was .81.

2.6 Measures of Internet Use Habits

Use of Devices
Questions referring to the use of devices (computers, tablets, smartphones, and consoles) during the day were also included (e.g., "*Indicate how many hours a day you use a tablet*").

Use of Social Networking Sites and Web Applications
Participants had to rank the five Internet tools (Facebook, Instagram, YouTube, WhatsApp, and Email) that they use the most during the day.

Time Connection and Interaction
The participants were asked to indicate how many hours are willing to devote to online activities during working and free time.

2.7 Data Analysis – Clustering

The hypotheses in this study were tested by considering groups of users with similar profiles. Instead of grouping study participants into pre-defined groups, clustering techniques were used to group users with similar profiles. The main advantage of this methodological approach is that the participant groups, i.e., different user profiles, emerged intrinsically from the data.

Indeed, in this study, clustering was approached in such a way that users with similar features/behaviors were grouped together into a cluster that differed from users in other clusters [20]. Two of the most commonly used clustering techniques are the K-means [31] and partitioning around medoids [25]. K-means clustering finds, iteratively, k centroids that define k clusters by assigning each individual to the cluster with the nearest centroid. The coordinates of each centroid correspond to the mean of the coordinates (features) of the users in the cluster, which prevents it from being used when categorical variables exist. Furthermore, K-means clustering is known to be sensitive to outliers [37]. Thus, K-medoids clustering is the most frequently adopted alternative method when the mean or median is not clearly defined or robustness to outlier data is required. K-medoids is similar to K-means but has medoids, i.e., representative individuals, instead of centroids. K-medoids minimizes the sum of medoids to cluster member distances. As medoids are actual data points in the data set, the K-medoids algorithm can be used in situations where the mean of the data is not present within the data set. Hence, K-medoids is useful for clustering categorical data where a mean is impossible to define or interpret.

Dissimilarity between individuals is measured as the distance between them. Assuming that we have data from n subjects with p variables (attributes, measures) that can be organized in matrix format as

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1p} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{np} \end{bmatrix},$$

a dissimilarity matrix is typically computed

$$\begin{bmatrix} 0 & & & \\ d(2,1) & 0 & & \\ d(3,1) & d(3,2) & 0 & \\ \vdots & \vdots & & \ddots & \\ d(n,1) & d(n,2) & \dots & d(n,n-1) & 0 \end{bmatrix},$$

where $d(i, j)$ is the dissimilarity between subjects i and j. Note that 0 imply that the subjects are equal and thus close to 0 means subjects are similar. Obviously this is a symmetric matrix with zeros in the diagonal ($d(i, i) = 0$). After computing this dissimilarity matrix, the goal is to group similar subjects.

Depending on the type of data available, different dissimilarity measures can be used. The most commonly used dissimilarity measure is the common distance (Euclidean) when variables are continuous. A measure commonly used when other than continuous variables are present is the Mahalanobis distance [32]. This is based on the correlations between variables with which different patterns can be identified and analyzed. It differs from Euclidean distance in that it takes into account the correlations of the data set and is invariant to scale, i.e., it does not depend on the scale of the measurements. If $x_i = (x_{i1}, x_{i2}, \dots, x_{ip})$ and

$x_j = (x_{j1}, x_{j2}, \ldots, x_{jp})$ are two data points, the Mahalanobis distance is defined as

$$d(x_i, x_j) = \sqrt{(x_i - x_j)^T S^{-1}(x_i - x_j)} \tag{1}$$

where S is the covariance matrix. Note that if S is the identity matrix, the Mahalanobis distance reduces to the Euclidean distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{p}(x_{ik} - x_{jk})^2}. \tag{2}$$

Because the data in this study also contained binary and categorical variables, an implementation of Partitioning around medoids (PAM) algorithm in MATLAB was used to identify emergent clusters in our data. Thus, the Mahalanobis distance was used as a dissimilarity measure. In order to find the optimal number of clusters, the K-medoids clustering algorithm was run for k = 2, 3, 4,.... The number of clusters chosen corresponds to the number of clusters for which the aggregate distance, from the medoids to the remaining elements that compose each cluster, no longer significantly reduces.

3 Results

Based on previous research, to test H1, the following variables were included in the construction of clusters: age, time connection, number of online contacts, use of devices (computers, tablets, smartphones, and consoles), use of networking tools (Facebook, Instagram, YouTube, WhatsApp, Email). For our data set, the optimal number of clusters was K = 3 (Table 1).

As Table 1 shows, Cluster 2 is composed of the youngest users who had, on average, the greatest number of contacts. This is also the profile that spent most time online. Users included in this profile were frequent users of YouTube, WhatsApp, and Facebook. They mostly accessed the Internet via computers and smartphones. Cluster 3 comprises the oldest users in the sample, who had, on average, the lowest number of contacts. Compared to the other profiles, this is the profile that spent least time online, but had more time available for interacting during work/study. Users included in this profile mostly accessed the Internet via computers, smartphones and tablets; they were infrequent users of Facebook and frequent users of WhatsApp and Email. Finally, Cluster 1 includes the young adult users. They spent less time online than the other profiles and were less willing to interact online both during work time and free time. These users accessed the Internet mostly via computers and smartphones and were frequent users of Facebook, WhatsApp and Email.

Table 1. Clusters description (variables presented were included in the cluster construction).

	Cluster 1	Cluster 2	Cluster 3
N	522	623	379
Quantitative variables	*M (SD)*	*M (SD)*	*M (SD)*
Age	33.83 (11.85)	25.79 (9.25)	36.80 (11.84)
Hours online	7.39 (5.90)	8.85 (6.35)	6.80 (5.98)
Hours interacting free time	6.63 (6.12)	8.35 (6.39)	8.67 (7.80)
Hours interacting work time	5.03 (5.50)	5.24 (6.02)	7.38 (7.06)
Number of Online contacts	849.89 (1501.29)	1080.37 (1885.78)	767.83 (1843.44)
Categorical variables	*n (%)*	*n (%)*	*n (%)*
Use of devices			
Computer	487 (93.3)	600 (96.3)	359 (94.7)
Tablet	161 (30.8)	158 (25.4)	243 (64.1)
Smartphone	479 (91.8)	561 (90)	335 (88.4)
Console	29 (5.6)	65 (10.4)	31 (8.2)
Use of SNS			
Facebook	512 (98.1)	580 (93.1)	87 (23)
Instagram	123 (23.6)	132 (21.2)	67 (17.7)
YouTube	4 (0.8)	623 (100)	105 (27.7)
WhatsApp	438 (83.9)	503 (80.7)	301 (79.4)
Email	397 (76.1)	391 (62.8)	265 (69.9)

Table 2. Differences between variables resulting from clusters.

Variables	Cluster 1		Cluster 2		Cluster 3		F	η^2
	M	SD	M	SD	M	SD		
PIU	2.28^a	1.12	2.82^b	1.35	2.03^c	1.08	79.14***	.10
Self-esteem	22.18^b	3.02	21.77^a	3.38	22.57^b	2.93	10.88***	.02
Self-control	45.98^a	7.26	42.52^b	7.74	46.56^a	8.04	45.72***	.06
Online social-support	2.85^a	1.07	3.04^b	1.02	2.73^a	1.12	34.45***	.05
Offline social-support	3.90	.04	3.88	.03	3.94	.04	1.24	.00
Mindfulness	4.21^a	.70	4.07^b	.68	4.31^a	.75	14.21***	.02
Cognitive absorption	3.80^a	.76	4.01^b	.72	3.73^a	.81	30.10***	.04
Life satisfaction	4.58^a	1.17	4.25^b	1.25	4.73^a	1.23	13.66***	.02
Job satisfaction	6.81	1.91	6.66	1.86	6.86	1.83	13.75***	.02
FIU	14.45^a	6.61	14.52^a	6.04	16.04^b	6.67	7.55***	.01

Note: Means with different letters are significantly different at the level of $\alpha <$ .05 according to the post-hoc test of Tuckey HSD. *** p < .001.

Testing of H2 and H3 was performed through ANOVAs (Table 2). F-tests indicated significant overall differences by cluster type at $p < .001$ on all variables considered, with the exception of offline social support. Post-hoc analyses indicated that Cluster 2 presented significant higher values on PIU, Online Social-Support and cognitive absorption, and significant lower values on Self-Esteem (while the difference with Cluster 1 was not significant), Self-Control, mindfulness, life satisfaction and functional Internet use (not significant different from Cluster 1). Moreover, post-hoc analyses also indicated that Cluster 1 is significantly different from Cluster 3 in two of the variables considered: PIU, for which it presents higher values, and FIU, where it presents lower values.

4 Discussion and Conclusions

This research set out to clarify when and how the use of the Internet and its applications/SNSs could become problematic or functional during a specific period of life characterized by different challenges. Since certain periods of life are associated with specific transitions and professional needs (see [4,21,22]), this may determine different profiles of digital technology use and, at the same time, the potential resources that characterize people's digital life may result in their functional or problematic use of technologies in dealing with those transitions. Thus, this research aimed to answer the questions: (RQ1) *Can transitions play a role in defining how and why people use digital technologies in different ways*? And, (RQ2) *can the period of life determine different profiles based on digital technology use*?

In order to achieve these objectives, three hypotheses were tested using cluster analysis for H1 and ANOVA for H2 and H3.

H1 (life periods of individuals, characterized by the transitions and challenges they face, influence how much they use ICT) was confirmed. As described in Table 1, Cluster 1 (mean age = 33.83) includes young adult users. They spent less time online than the other profiles and were less willing to interact online during both work/study time and free time; they access the Internet mostly via computers and smartphones and were frequent users of Facebook, WhatsApp and Email. Indeed, many subjects in Cluster 1 already had a job and mainly use social networks and chats to maintain contact with their peer group. Cluster 2 (mean age = 25.79) is the profile that had, on average, the greatest number of online contacts and was also the profile that spent most time online, via computer and smartphone. Indeed, this age group, which coincides with the younger emerging adults [3,4], is recognized as experiencing a period of life characterized by great challenges and changes. From this viewpoint, the Internet plays a significant role as a means of constructing a bridge between school and university or school and the working environment [7,36]. Moreover, users included in this profile were frequent users of YouTube, WhatsApp, and Facebook. In this regard, SNSs are also fundamental as a means of pre-socialization during transitions towards the new environment and connecting with those who are already a part of that system. Finally, Cluster 3 (36.80) is constituted by the oldest users in the sample, who had, on average, the lowest number of contacts compared to the other clusters. This profile spent least time online, but is most willing to spend time interacting during work time. This suggests that the adult cluster uses the Internet principally for work and less during free time. Indeed, these users mostly accessed the Internet via computers, smartphones and tablets, and they were frequent users of WhatsApp and Email.

H2 (dysfunctional use of the Internet could change during life based on the challenges linked to life transitions) was partially confirmed: the results show that Cluster 2 (the youngest subjects) has higher values on PIU, Online Social Support and cognitive absorption (although the difference with Cluster 1 was not significant), Self-Control, mindfulness, life satisfaction and functional Internet use (not significantly different from Cluster 1). These results tend to confirm the social compensation hypothesis: since Emerging Adults are constructing their professional identity, they are characterized by instability, exploration, and change. These dynamics could affect self-esteem, since this profile can encounter many failures, posing the need for further social support and for sharing information and knowledge. This behavior poses a potential risk if individuals perceive online contexts as the simplest way to compensate for these shortcomings.

Finally, H3 (functional use of the Web could change during life based on the challenges people are facing) is confirmed, as the highest significant scores in FIU are those of Cluster 3. Indeed, this group is the one having already achieved many life goals, is the most stable and, following the model described in Figs. 1 and 2, has the most potential resources at their disposal.

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