

Academic Procrastination, Digital Addiction, and General Achievement Expectancy in University Students: Profile Delineating via Hierarchical Cluster Analysis

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Article

Keywords: academic procrastination, digital addiction, general achievement expectancy, hierarchical cluster analysis, higher education students

Posted Date: September 8th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9968475/v1>

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Additional Declarations: No competing interests reported.

Abstract

This study aims to determine meaningful student profiles via hierarchical cluster analysis based on the patterns formed by academic procrastination (AP), digital addiction (DA), and general achievement expectancy (GAE) variables in university students. Utilizing a person-centered approach, the research was conducted with 508 university students. Hierarchical cluster analysis, using Ward's method and Euclidean distance, revealed two distinct main profiles: the 'Procrastinating - Digital Addicted Group' and the 'Digital Balanced - Success Oriented Group'. The procrastinating-digital addicted profile exhibited simultaneously high levels of digital addiction and academic procrastination, along with lower general achievement expectancy. In contrast, the digital balanced-success oriented group was characterized by low procrastination and addiction scores, and a significantly higher general achievement expectancy. Demographic analyses indicated that the effect of these profiles on academic procrastination varied by department; students in Social and Physical Sciences displayed significantly higher procrastination behaviors compared to those in Theology, Arts and Sports, and Linguistics. Furthermore, digital addiction and procrastination levels were significantly lower in students aged 23 and above, while this older age group within the digital balanced profile demonstrated significantly higher achievement expectancies. The findings suggest that universities should move away from "one size fits all" approaches and design targeted, profile-specific prevention and educational interventions based on students' digital risk and academic belief combinations.

Introduction

Our interactions with digital technologies in daily life are increasing every day with the diversification of digital platforms and content. Especially for students studying at the higher education level, it is possible to state that their interactions with these technologies have significantly increased, both to acquire the digital competencies created by the digital transformation in labor markets and due to the digitalization of education and teaching processes. As many activities, from accessing course materials to group work and from assessment-evaluation processes to social interactions, move to online channels, the self-regulation skills expected of students to achieve their career goals and general achievement expectations are gaining importance.

Along with intense interaction with digital technologies, the problematic use of these technologies can lead to the emergence of digital addiction (DA) problem. Conceptually, DA is defined as the uncontrollable increase in the use of digital tools and platforms such as the Internet, social media, smartphones, and online games, and the onset of disruption in daily life functionality in contexts such as academic, social, emotional, and physical (Karakose, Tülübaş & Papadakis, 2022). It can be considered that DA, arising from problematic digital technology use, may lead higher education students to acquire academic procrastination habits and, as a natural consequence, may affect their general achievement expectancies.

Academic procrastination (AP) is a widespread behavioral pattern that indicates disruptions in self-regulation processes and emerges through the conscious delay of intended academic tasks, rather than being a simple habit seen merely as an "inefficient use of time" (Steel, 2007). Because this situation delays progress toward goals and accumulates stress for higher education students, it can yield negative consequences on academic performance and well-being in the long run. Studies addressing the causes of academic procrastination in recent years have focused more on the quality of the relationship students establish with digital technologies (Nadarajan et al., 2023; Parmaksız, 2022; Savaş et al., 2025; Touloupis & Campbell, 2024; Ulutaş Deniz et al., 2025; Wu et al., 2025). In particular, the state of "being constantly connected" via social media and smartphones can divide attention resources, making non-task online activities more easily accessible and attractive (Parmaksız, 2022; Wu et al., 2025).

When conducted research is examined, while it reveals that the problematic use of mobile phones, one of the most preferred tools for interacting with digital technologies, is associated with academic burnout and that digital risks can show consistent effects on academic functionality, it is understood that there is a positive relationship between smartphone addiction and procrastination tendencies. (Chen & Lyu, 2024; Li et al., 2023; Zhou et al., 2024). This suggests that procrastination is not limited to a "time management" issue but can be intertwined with processes such as cognitive fatigue, motivational conflict, and burnout.

It is possible to state that the effect of digital risks on academic outcomes has a complex mechanism. Digital burnout is directly related to academic procrastination, whereas life satisfaction and fatigue play important mediating roles in this interaction (Savaş et al., 2025). In this process, it is emphasized that as internet use intensifies, procrastination and problematic use feed each other (Nadarajan et al., 2023; Ulutaş Deniz et al., 2025), and digital environments function as an "avoidance" mechanism, especially in cases where self-control is low (Geng et al., 2018). Similarly, when problematic social media use is considered together with protective factors such as academic engagement, its power to explain procrastination increases (Touloupis & Campbell, 2024), and it can be stated that there is a reciprocal and cyclical relationship between smartphone addiction and procrastination over time (Lin et al., 2025).

Notifications caused by smartphones and the content interacted with via this technology, multitasking habits, and the intensity of online stimuli can be characterized as situations that can affect attention control. Findings showing that smartphone use and self-control explain academic outcomes together indicate that digital use should not be considered alone but together with individual self-regulation resources (Troll et al., 2021). In contrast, the effect of digital behaviors on academic procrastination may not be at the same level for everyone. It is reported that this effect can strengthen or weaken depending on individual resources, such as self-control, academic self-efficacy, and similar factors (Farhadi Rad et al., 2025; Kim et al., 2025; Parmaksız, 2022; Troll et al., 2021). For example, the mediating role of resources in the relationships between social media use and academic outcomes shows that the effect of digital environments can vary from student to student (Kim et al., 2025).

Understanding this relationship, general achievement expectancy (GAE), which represents students' expectations and beliefs in the academic field, is particularly important. GAE reflects a student's general evaluation regarding their success in academic goals and their ability to cope with academic demands. Such expectations and beliefs are guiding in terms of self-regulation. An individual starts a task more easily when they say, "I can do it," sustains it for a longer time, and can make task-related negative emotions more manageable. Therefore, GAE is a protective resource against procrastination and can reduce the negative impact of digital distractors. Academic self-efficacy is negatively related to procrastination and, together with emotional regulation difficulties, explains procrastination at a significant level (Farhadi Rad et al., 2025). Similarly, it has been shown that intrinsic learning motivation and academic self-efficacy can play a serial mediating role in the relationship extending from social support to procrastination (Chen et al., 2025). These findings suggest that expectancy/belief variables, such as GAE, are not only a direct predictor but may also be a psychological resource that shapes the processes through which students handle academic tasks under digital risk conditions.

However, a significant limitation in the literature is that relationships are mostly handled from a variable-centered perspective (e.g., correlation, regression, or structural equation models). Such analyses are strong in showing average trends and general directions of relationships ; however, they can easily overshadow the fact that university students are not a homogeneous group in terms of digital behaviors, procrastination, and achievement expectancy. For example, while two of the students exhibiting similar levels of DA can start academic tasks on time thanks to high GAE, the other may quickly turn small distractions into procrastination behavior due to low GAE. Similarly, while the main problem in some students showing high AP is attention division caused by DA, in some students, low achievement expectancy and the tendency to avoid task-related negative emotions may come to the fore. Therefore, instead of "a single average effect," it is thought that person-centered approaches, which make student profiles where different risk/protective combinations are seen together visible, could be more explanatory.

Person-centered analyses performed with clustering or profile-based approaches gather similar individuals in the same group by considering patterns formed by multiple variables, thus allowing for the definition of meaningful subgroups among students. Studies that have examined patterns related to procrastination in university samples using LPAR have demonstrated the applicability of this approach (Kokkinos et al., 2023). Through analyses performed on a profile basis, it is possible to determine which student group could benefit more from which type of prevention and intervention strategy. In this context, when the relevant literature is examined, although AP, DA, and GAE variables are frequently discussed through bilateral relationships, studies on how the combinations formed by this trio cluster in student groups are limited. In contrast, while variable-centered findings provide average trends, the question of "who has which pattern?", which could be more functional in terms of application and intervention design, often remains unanswered. Although it is necessary to avoid causality, especially in the interpretation of cross-sectional findings, the distinguishing role of cognitive resources such as ES (expectancy of success) in students with similar digital risk levels needs to be addressed in more detail at the level of person-centered patterns.

The main purpose of this study is to determine meaningful student profiles via hierarchical cluster analysis based on the patterns formed by academic procrastination (AP), digital addiction (DA), and general achievement expectancy (GAE) variables in university students. The study aims, on the one hand, to address the relationships between AP and DA holistically in the context of GAE and to define heterogeneous student groups by going beyond variable-centered findings. Thus, this study presents an evidence-based framework for designing prevention and educational interventions more specifically in the university context by making student profiles with different combinations of digital risks and academic beliefs visible.

METHOD

This research employed a quantitative, cross-sectional design to investigate the relationships between academic procrastination, digital addiction, and general achievement expectancy among university students. To move beyond variable-centered averages, a person-centered methodology was adopted to identify and define distinct behavioral profiles within the sample. The following subsections detail the data collection instruments, the procedures followed during the data collection phase, and the statistical techniques utilized for data analysis.

Data Collection Tools: In this study, quantitative data were collected utilizing three distinct measurement tools. The participants' academic procrastination behaviors were measured using the Revised A Procrastination Scale-15, which was revised and adapted into a 15-item structure by Tatar, Saltukoğlu, and Özdemir (2019) to measure general procrastination levels. The scale evaluates procrastination across three sub-dimensions: Cognitive, Behavioral, and Emotional, utilizing a 5-point Likert-type grading system. In the adaptation study, the internal consistency reliability coefficient (Cronbach's alpha) for the entire scale was calculated as 0.912. Example items from the scale include "I finish the tasks I take on on time," "I usually delay the tasks I have to do," and "I usually handle my tasks at the last minute". The digital addiction levels of the students were determined using the Digital Addiction Scale developed by Kesici and Tunç (2018). This 19-item scale features five sub-dimensions: Overuse, Non-restraint, Inhibiting the Flow of Life, Emotional State, and Dependence, and responses are recorded on a 5-point Likert scale ranging from "Totally Disagree" to "Totally Agree". The developers reported a Cronbach's alpha reliability coefficient of 0.874 for the complete scale. Sample items from this instrument include "While eating my meal, I am occupied with mobile phone, tablet, or computer," "I overuse the digital devices out of their purposes," and "I find myself checking my digital devices upon dealing with a work". To assess the students' beliefs regarding their future achievements, the Generalized Expectancy for Success Scale (GESS-R) was administered. Originally developed by Fibel and Hale (1978) and later revised by Hale, Fiedler, and Cochran (1992), the scale was adapted into Turkish culture by Çelik Ercoşkun, Ozan, and Kincal (2019). The Turkish adaptation comprises 21 items on a 5-point Likert-type structure and measures success expectations through three sub-dimensions: Individual expectation, Social interaction, and Failure. The Cronbach's Alpha internal consistency coefficient for the adapted Turkish version was reported to be 0.87 for the whole scale. Example items include "In the future I expect

that I will succeed at most things I try," "In the future I expect that I will carry through my responsibilities successfully," and "In the future I expect that I will experience many failures in my life".

In the current study, the internal consistency reliability coefficients (Cronbach's alpha) were recalculated to confirm the reliability of the measurements for the present sample. The Cronbach's alpha values were determined as 0.926 for the Revised A Procrastination Scale-15, 0.910 for the Digital Addiction Scale, and 0.867 for the Generalized Expectancy for Success Scale. These results indicate a high level of reliability for all instruments utilized in this research.

Data Collection: The data for this study were collected during the fall semester of the 2025–2026 academic year. The participant pool comprised undergraduate students enrolled at two different universities located in the Marmara and Black Sea regions of Turkey. The entire data collection process was conducted and completed over a period of approximately one month. Prior to the data collection phase, ethical approval was granted by the Sakarya University Educational Research and Publication Ethics Committee (Approval Number: E-61923333-050.99-571740), and necessary permissions were obtained from the relevant university administrations. All methods were carried out in accordance with relevant guidelines and regulations. The data were collected utilizing a self-report survey method. Before administering the measurement instruments, the researchers thoroughly briefed the prospective participants about the primary objectives of the study. It was explicitly emphasized that participation was strictly voluntary and that all collected data would be kept confidential and used solely for scientific research purposes. Written informed consent was obtained from all students who agreed to participate. Following the consent process, the participants completed a survey battery that included a demographic information form along with the scales assessing Academic Procrastination, Digital Addiction, and General Achievement Expectancy. Forms with missing or incomplete data were excluded from the dataset, yielding a final sample of 508 valid responses for the statistical analyses.

Data Analysis: Cluster analysis is a grouping process that combines a large number of objects, phenomena, or people based on their similar characteristics, while separating them from other groups as much as possible (Ward, 1963). Generally, two approaches are used in cluster analyses: agglomerative and divisive (Kassambara, 2017; Airoldi, Blei, Erosheva, & Fienberg, 2014).

Agglomerative clustering follows a bottom-up approach; in the first step, every object, phenomenon, and event is evaluated as a group on its own. The algorithm combines the clusters that are most similar to each other in terms of specific characteristics at each step, and this process continues until all clusters are united under a single cluster (Kassambara, 2017). In divisive clustering, in the first step, while all objects, phenomena, and events are within a large cluster, the algorithm continues by separating dissimilar clusters at each step until each object forms its own cluster (Airoldi, Blei, Erosheva, & Fienberg, 2014).

In this study, agglomerative clustering was used with Ward's method as the linkage criterion and Euclidean distance as the distance metric (dissimilarity measure).

FINDINGS

This section presents the research findings.

Demographic Characteristics

Table 1
Demographic Information of Participants

Variable	Category	n	%
Gender	Female	400	78.7
	Male	108	21.3
Age	23 years and above	248	48.8
	20 years and below	188	37.0
	21–22 age group	72	14.2
Department Field	Social Sciences	325	63.9
	Physical Sciences	87	17.1
	Linguistics	34	6.7
	Theology	33	6.5
	Arts and Sports	29	5.7

The demographic characteristics of the 508 university students participating in the research are detailed in Table 1. 78.7% of the participants are female (n = 400) and 21.3% are male (n = 108). This ratio indicates that the sample is predominantly female in terms of gender. When the age distribution of the participants is examined, 48.8% are 23 years of age or older (n = 248), 37.0% are 20 years of age or younger (n = 188), and 14.2% are in the 21–22 age group (n = 72). This finding indicates that the sample is largely concentrated in the older age group.

Regarding field of study, it was found that the majority of the participants (n = 325; 63.9%) studied in the field of social sciences, followed by physical sciences (n = 87; 17.1%), linguistics (n = 34; 6.7%), theology (n = 33; 6.5%), and arts and sports (n = 29; 5.7%).

Correlation Between Variables

The relationships between digital addiction, academic procrastination, and general achievement expectancy variables included in the study were examined using Pearson’s correlation analysis. According to the results obtained, a moderate positive relationship (r = .48) was found between digital

addiction and academic procrastination; this indicates that individuals with high digital addiction also have high tendencies to procrastinate on academic tasks.

As illustrated in Fig. 1, a moderate negative relationship ($r = -.47$) was detected between general achievement expectancy and academic procrastination; this result revealed that individuals with high achievement expectancy are less inclined to exhibit academic procrastination behavior. Furthermore, a moderate negative relationship ($r = -.42$) was observed between general achievement expectancy and digital addiction, indicating that as individuals' levels of digital addiction increase, their belief in future success decreases.

Hierarchical Cluster Analysis

Three different validity measures—the Davies–Bouldin index, gap statistic, and silhouette score—were used to determine the optimum number of clusters in the cluster analysis.

As presented in Fig. 2 regarding the validity measures, the results obtained using all three criteria revealed that the most appropriate number of clusters was two ($k = 2$). The Davies–Bouldin index yielded the lowest value for $k = 2$, reflecting the situation in which the separation between clusters and internal consistency were strongest. Similarly, when the gap statistic was examined, the highest value was again observed at $k = 2$, indicating that the clustering structure differed significantly from the reference model. Silhouette scores also yielded the highest value for $k = 2$, supporting the existence of a distinct separation and high internal consistency between the clusters. In line with these findings, it was concluded that there were two distinct subgroups within the dataset.

When the hierarchical cluster dendrogram presented in Fig. 3 is examined, it is evident that the participants are divided into two main clusters. The distance values shown on the vertical axis reflect the level of similarity between clusters; in this context, the cut-off point shown with the red dashed line was determined at approximately 20 distance units, and this level indicates that the samples are meaningfully separated into two large groups. The structure of the dendrogram reveals that there are more homogeneous groups with shorter connections (in the lower branches) within the clusters, whereas at the upper level, these groups are gathered under two distinct main clusters. This structure supports that the optimum number of clusters ($k = 2$) obtained from the previous validity analyses is accurately reflected. Accordingly, it can be stated that the participants are divided into two meaningful profiles according to their levels of digital addiction, academic procrastination, and general achievement expectancy.

After this stage, it was decided which of the sklearn and scipy libraries would be used for the hierarchical cluster analysis by examining the compatibility indices between the two libraries. based on the compatibility indices analysis presented in Table 2, full compatibility was detected between the two libraries used in terms of hierarchical cluster analysis; therefore, we continued the hierarchical cluster analysis with the sklearn library.

Table 2
Sklearn and Scipy Libraries Compatibility Indices

Consistency Index	Value
Adjusted Rand Index	1.0000
Normalized Mutual Information	1.0000
Fowlkes-Mallows Index	1.0000
Mapping Accuracy (Majority Mapping)	1.0000
Purity	1.0000

The results of the hierarchical cluster analysis are presented as follows.

As a result of the hierarchical cluster analysis, participants were gathered under two main profiles that distinctly diverge according to their Academic Procrastination (AP), Digital Addiction (DA), and General Achievement Expectancy (ES) levels (Fig. 4). These profiles have been named the '**Procrastinating - Digital Addicted Group**' and the '**Digital Balanced - Success Oriented Group**' according to the characteristic features they exhibit.

- **Procrastinating – Digital Addicted Group (Orange Line):** Individuals in this group exhibited statistically higher averages in academic procrastination and digital addiction variables than in the other group. This profile represents a risk group in which the level of digital addiction and academic procrastination behavior simultaneously increased. Furthermore, in relation to the height of these negative variables, it was observed that the group's general achievement expectancy level remained lower than that of the 'Digital Balanced' group.
- **Digital Balanced–Success Oriented Group (Blue Line):** This group is characterized by low academic procrastination and low digital addiction scores. The most striking feature of the group is that, inversely proportional to the low levels of procrastination and addiction, it shows a sharp increase in general achievement expectancy (ES) scores and reaches the highest average.

Consequently, the analysis reveals that the 'Digital Balanced - Success Oriented' profile, in which digital addiction and academic procrastination behaviors are kept under control, is the most critical factor positively differentiating the beliefs and expectations of future success.

Descriptive statistics for these profiles are provided below.

Table 3
Descriptive Statistics of Profiles

Academic Procrastination								
	N	X (Mean)	std	min	25%	50%	75%	max
Digital Balanced - Success Oriented Group	302	27.86	6.895	15	23	29	32	48
Procrastinating - Digital Addicted Group	206	42.28	8.939	15	37	43	48	70
Digital Addiction								
	N	X (Mean)	std	min	25%	50%	75%	max
Digital Balanced - Success Oriented Group	302	44.33	8.632	23	38	45	50	64
Procrastinating - Digital Addicted Group	206	60.54	10.15	25	53.25	59.5	67	90
General Achievement Expectancy								
	N	X (Mean)	std	min	25%	50%	75%	max
Digital Balanced - Success Oriented Group	302	85.7	6.810	73	81	85	90	105
Procrastinating - Digital Addicted Group	206	77.1	6.231	62	73	77	81	96

When the descriptive statistics of the obtained profiles are examined, significant differences are observed between the groups. According to the data presented in Table 3, it was determined that the averages of both academic procrastination ($X = 42.28$) and digital addiction ($X = 60.54$) of the participants in the cluster named Procrastinating - Digital Addicted Group were quite high compared to the Digital Balanced - Success Oriented Group ($X = 27.86$ and $X = 44.33$, respectively). In contrast, in terms of the General Achievement Expectancy variable, the 'Digital Balanced - Success Oriented Group' ($X = 85.7$) has a higher average than that of the other group ($X = 77.1$). These results support the characteristic distinctions in the naming of the groups based on quantitative data.

The results of the analysis conducted to determine whether this emerging descriptive profile indicates a statistically significant separation and to test the distribution characteristics of the data are presented below.

Table 4
Normality Assumptions, Dispersion Measures, and Group Comparisons of Created Profiles

IQR		AP	DA	ES
	Digital Balanced - Success Oriented Group	9	12	9
	Procrastinating - Digital Addicted Group	11	13.75	8
Skewness	Digital Balanced - Success Oriented Group	0.011	-0.153	0.563
	Procrastinating - Digital Addicted Group	-0.34	0.18	0.37
Kurtosis	Digital Balanced - Success Oriented Group	-0.41	-0.37	-0.27
	Procrastinating - Digital Addicted Group	0.34	0.39	0.53
MAD	Digital Balanced - Success Oriented Group	5	6	5
	Procrastinating - Digital Addicted Group	5.5	6.5	4
F (p)		419.65 (0.00)	373.94 (0.00)	209.97 (0.00)

When the Table 4 is examined, first of all, it is seen that the distribution characteristics of the data set meet the assumptions of parametric tests. Skewness and kurtosis values for academic procrastination (AP), digital addiction (DA), and general achievement expectancy (ES) variables for both groups are within acceptable limits (e.g., ± 1.5 range). When dispersion measures, such as the interquartile range (IQR) and median absolute deviation (MAD), are examined in addition to measures of central tendency, it is confirmed that the groups exhibit a consistent and homogeneous structure within themselves, and the representation power of the mean values is high.

At this point, only in the 'Digital Addiction (DA)' dimension, the fact that the IQR (13.75) and MAD (6.5) values of the Procrastinating - Digital Addicted group are relatively higher than the Digital Balanced - Success Oriented group (IQR = 12; MAD = 6) indicates that the behavioral diversity in the risky group is spread over a wider range.

When the inter-group differentiation was tested on the basis of these structural features of the data set, it was determined that the created clusters differed at a statistically significant level in terms of all three variables ($p < .001$). The magnitude of the calculated F values ($F_{AP} = 419.65$; $F_{DA} = 373.94$; $F_{ES} = 209.97$) shows that the variance between groups is considerably higher than the within-group variance;

thus, it proves that the Digital Balanced - Success Oriented and Procrastinating - Digital Addicted groups are separated by clear lines.

Two-way analysis of variance (ANOVA) was applied to determine whether the 'Digital Balanced - Success Oriented' and 'Procrastinating - Digital Addicted' profiles obtained as a result of hierarchical cluster analysis differed according to the type of department the participants were studying in (Social, Physical, Linguistics, Theology, Arts and Sports). In this analysis, 'Cluster Groups' and 'Department' were included in the model as independent variables, whereas general achievement expectancy, digital addiction, and academic procrastination scores were examined as dependent variables. The analysis was conducted to test whether the effect of the determined student profiles on the variables in question changed depending on the department studied (interaction effect).

Table 5
Two-Way ANOVA Results According to General Achievement Expectancy, Digital Addiction, and Academic Procrastination Cluster Profiles and Department Variable

Dependent Variable	Source	Sum of Sq.	df	Mean Square	F	p	np2
General Achievement Expectancy	Group (Clusters)	3014.79	1	3014.79	70.70	< .001	.12
	Department	47.05	4	11.76	0.28	.894	.00
	Group * Department	253.05	4	63.26	1.48	.206	.01
	Error	21236.71	498	42.64			
Digital Addiction	Group (Clusters)	7235.43	1	7235.43	87.58	< .001	.15
	Department	967.01	4	241.75	2.93	.021	.02
	Group * Department	396.34	4	99.09	1.20	.310	.01
	Error	41142.44	498	82.62			
Academic Procrastination	Group (Clusters)	5933.68	1	5933.68	100.68	< .001	.17
	Department	846.01	4	211.50	3.59	.007	.03
	Group * Department	583.02	4	145.76	2.47	.044	.02
	Error	29350.95	498	58.94			

The results of the two-way analysis of variance (ANOVA) presented in Table 5 showed that the joint interaction of the 'Group' and 'Department' variables did not lead to a significant differentiation in general achievement expectancy ($F(4, 498) = 1.48, p > .05$) and digital addiction ($F(4, 498) = 1.20, p > .05$).

However, the interaction between Group and Department on academic procrastination scores was found to be statistically significant ($F(4, 498) = 2.47, p < .05$). This finding reveals that the effect of having a 'Digitally Balanced-Success Oriented' or 'Procrastinating-Digitally Addicted' profile on academic procrastination behavior varies according to the department in which the student is studying.

The results of the Tukey HSD multiple comparison test, which was used to determine the source of this significant differentiation observed in academic procrastination scores and to determine between which departments there was a statistically significant difference, are presented below.

Table 6
Multiple Comparison (Tukey HSD) Results of Academic Procrastination Scores
According to Departments

(I) Department	(J) Department	Mean Difference (I-J)	Sig. (p)
Social Sciences	Physical Sciences	0.36	.995
	Linguistics	5.09*	.002
	Theology	7.46*	.001
	Arts and Sports	6.12*	.001
Physical Sciences	Social Sciences	-0.36	.995
	Linguistics	4.73*	.020
	Theology	7.10*	.001
	Arts and Sports	5.76*	.005
Linguistics	Theology	2.37	.714
	Arts and Sports	1.03	.984
Theology	Arts and Sports	-1.34	.959

When Table 6 is examined, no significant difference was found between the Social and Physical Sciences departments; however, it was determined that the procrastination scores of these two departments were statistically significantly higher than those of the Theology, Arts and Sports, and Linguistics departments ($p < .05$). According to the analysis performed, while students in the Procrastinating - Digital Addicted group who are in the Theology, Arts, and Linguistics departments are more successful in completing their homework and tasks on time, academic procrastination behavior is significantly more common in students in the Social and Physical Sciences fields.

Table 7
Two-Way ANOVA Results According to General Achievement Expectancy, Digital Addiction, and Academic Procrastination Cluster Profiles and Age Variable

Dependent Variable	Source	Sum of Sq.	df	Mean Square	F	p	η^2
General Achievement Expectancy	Group (Clusters)	5399.82	1	5399.82	126.56	< .001	.20
	Age Group	112.68	2	56.34	1.32	.268	.01
	Group * Age Group	308.78	2	154.39	3.62	.028	.01
	Error	21376.49	501	42.67			
Digital Addiction	Group (Clusters)	22025.26	1	22025.26	266.11	< .001	.35
	Age Group	1600.24	2	800.12	9.67	< .001	.04
	Group * Age Group	221.67	2	110.83	1.34	.263	.01
	Error	41466.54	501	82.77			
Academic Procrastination	Group (Clusters)	16418.05	1	16418.05	278.84	< .001	.36
	Age Group	981.07	2	490.54	8.33	< .001	.03
	Group * Age Group	147.18	2	73.59	1.25	.287	.01
	Error	29499.11	501	58.88			

The analysis results presented in Table 7 reveal that the joint interaction of the 'Group' and 'Age Group' variables on Digital Addiction and Academic Procrastination variables was not significant ($p > .05$). However, the main effects of both the group (profile) and age were statistically significant in both variables ($p < .001$). Post-hoc examinations indicate that the digital addiction and academic procrastination levels of students aged 23 years and older are significantly lower than those of younger age groups (20 years and below, and 21–22 years old).

In contrast, the interaction effect of Group and Age variables on General Achievement Expectancy scores was found to be significant ($F(2, 501) = 3.62, p < .05$). This finding reveals that the effect of being in the Digital Balanced-Success Oriented or Digital Addicted-Procrastinating profile on achievement expectancy changes depending on the student's age, and that the role of the age factor on achievement expectancy differs according to the digital profile the student possesses.

The results of the Tukey HSD multiple comparison test, which was used to determine the source of this significant difference and which groups showed a significant difference, are presented below.

Table 8
Multiple Comparison (Tukey HSD) Results of General Achievement Expectancy Scores
According to Age Groups

(I) Age Group	(J) Age Group	Mean Difference (I-J)	Std. Error	P
20 years and below	21–22 years	-1.14	.91	.419
	23 years and above	-3.45*	.63	.001
21–22 years	20 years and below	1.14	.91	.419
	23 years and above	-2.31*	.87	.023
23 years and above	20 years and below	3.45*	.63	.001
	21–22 years	2.31*	.87	.023

When the results of the Tukey multiple comparison test presented in Table 8, performed to determine the source of the difference between general achievement expectancy scores according to the age variable are examined, it was observed that the general achievement expectancy scores ($X = 83.86$) of the 23 years and above group located in the Digital Balanced-Success Oriented group were statistically significantly higher than both the 20 years and below ($X = 80.41$) and 21–22 years ($X = 81.56$) groups ($p < .05$). In contrast, no significant difference was found between the 20 years and below group and the 21–22 years group in terms of general achievement expectancy ($p > .05$). This finding shows that as the age and academic experience of students in the digital balanced and general achievement expectancy profile increase (especially at the maturity level of 23 years and above), their achievement expectancies also rise significantly

DISCUSSION

Person- Centered Profiles

This study was designed to identify distinct student groups by using hierarchical cluster analysis to identify different student groups based on the combination of three variables: academic procrastination (AP), digital addiction (DA), and general achievement expectancy (GAE), from a group of university students. Two student groups were identified as being statistically significant or having a clear distinction between them: the procrastinating–digital addicted group and the digital balanced–success orientation group. These two student groups provide further support and extend the growing body of literature supporting a person-centered approach, indicating that students attending universities are not a homogenous group regarding their self-regulatory and digital behavioral patterns.

The person-centered approach used in this research has high relevance. Variable-centered methodologies, that is, correlation or regression analyses, report on aggregate tendencies of samples, which may mask the existence of meaningful within-sample variability. In this respect, the results found in this study agree with those reported by Gross et al. (2024), who applied latent profile analysis to

doctoral students, identifying qualitatively discrete types of students ranging from highly productive self-regulators to anxiety-laden procrastinators, and concluded that interventions should be type-specific instead of being universal. In addition, Klingsieck (2013) stated that the search for procrastination "types" will offer a more practical basis for designing targeted intervention programs than the search for means of variable associations. The person-centered approach of this study agrees with these recommendations by providing insights into how the same level of digital risk may occur with very different motivational profiles.

The two-profile solution found in this study is similar to the dualistic type that has been described with the same typologies in the literature on academic procrastination in undergraduates using latent profile analysis. Specifically, studies employing conscientiousness, procrastination, and evaluative concerns for classification purposes have often identified a group of students who are well-functioning and have little procrastination and a group of students who are maladaptively functioning and have high levels of procrastination (Mastrokoulou et al., 2025). Therefore, the clarity and strong statistical evidence for the two-cluster solution in this study—using Davies–Bouldin, gap statistic, and silhouette methods— further support the validity of the two profiles.

Digital Addiction and Academic Procrastination

A moderate but statistically significant positive relationship ($r = .48$) was found in this study between digital addiction and academic procrastination, where those in the Procrastinating – Digital Addicted group scored significantly higher than their peers on both variables. The current results corroborate previous studies that have identified a strong reciprocal link between problematic digital use and academic delay behavior. This was demonstrated by Nadarajan et al. (2023), who used a cross-sectional design to show that there was a significant positive correlation between Internet addiction and academic procrastination in a sample of 470 Thai university students, and further that procrastination was a predictor of Internet addiction. Similarly, Lin et al. 's (2025) finding, using cross-lagged panel modeling, showed that smartphone addiction and procrastination were positively correlated with each other, as well as each being a positive predictor of the other across time for a sample of Chinese college students, supporting the idea of a cycle of digital and procrastination.

Resource depletion theory explains some of the mechanisms by which excessive Internet use relates to an increase in procrastination. Online activities drain mental and emotional energy, which makes completing academic obligations more likely to be delayed (Wu et al., 2025). Furthermore, Wu et al. (2025) demonstrated that Internet addiction has an indirect, serial relationship with procrastination by reducing self-control and increasing anxiety. Reduced self-control increases anxiety, which in turn increases procrastination. This model is consistent with the findings of Tang and He (2025), who demonstrated a mediating model in which fear of missing out (FOMO) and self-control are the chain mediators; that is, Internet addiction influences procrastination by decreasing self-control and increasing FOMO; thus, students who spend large amounts of time on digital platforms have increased difficulty beginning and sustaining academic tasks.

Özbay et al. (2025) examined how nomophobia, netlessphobia, and attention control predict academic procrastination and contributed to the literature by investigating these relationships in the Turkish higher education setting. They showed that nomophobia, netlessphobia, and attention control explained a large portion of the variation in academic procrastination. For them, the biggest independent predictor of academic procrastination was attention control, an executive self-regulation resource expected to decrease with the excessive use of digital technologies. This finding is consistent with our previous claim that high levels of procrastination among students in the Academic Procrastination-Digital Addiction group represent not merely a coincidental common variance, but rather a functional clustering of depleted self-regulation resources.

General Achievement Expectancy

The most theoretically significant finding of the study was that general achievement expectancy (GAE) was the primary factor that separated the two profile groups. In addition to having lower DA and AP scores, the digital balanced-success oriented group had a significantly higher GAE mean ($M = 85.7$) than the risk group ($M = 77.1$). Although the F value for GAE between the groups ($F = 209.97$; $p < .01$) was lower than the values for DA and AP, it represented a considerable difference between the groups, indicating that GAE can be a discriminant resource even after digital and procrastination factors were taken into consideration.

These results reflect research demonstrating that academic self-efficacy and expectancy beliefs are protective factors against procrastination. Rad et al. (2025) showed that academic self-efficacy predicted procrastination in a direct path model, and that the effect was further mediated by difficulties in emotional regulation. Students who have positive confidence in their ability to achieve their goals can begin tasks, tolerate the affect associated with those tasks, and continue to work through challenges, each of which represents one of the primary behavior deficits that characterize procrastination. The negative relationship between GAE and DA ($r = -.42$) identified in this study also shows that students who have high achievement beliefs may be less likely to engage in escapist behaviors using digital media; this result supports the finding by Tang and He (2025) that self-control that has been shown to be lower among individuals with weaker self-efficacy appraisals represents a critical mechanism through which procrastination arises when individuals are addicted to social media.

The theory behind the GAE construct used in this study has some similarities to Wigfield & Eccles' (2000) Expectancy-Value Model; where the expectancy element (i.e., "Can I succeed?") acts as a motivational regulator of the degree of engagement in tasks. Therefore, the students classified as part of the Digital Balanced–Success Oriented group may have lower levels of DA not only due to using digital platforms at lower frequencies, but also due to their high degree of confidence regarding their success, which may make digital environments less reinforcing for avoiding the experience of failure. This interpretation aligns with the findings of Kim et al. (2025) that social media usage and academic performance are moderated by grit, a trait related to GAE in its emphasis on goal-oriented tenacity, and the results from

Troll et al. (2021), indicating that the effects of using smartphones and self-regulation, as separate constructs, on academic performance were additive rather than multiplicative.

Departmental Differences

The two-way ANOVA results showed that there was an interaction effect ($F(4, 498) = 2.47, p < .05, \eta^2 = .02$) between cluster groups and academic departments on the AP dimension; therefore, the degree of group membership that exhibits procrastination behavior differs depending on the academic department. The post hoc analysis of this interaction indicated that procrastination scores were higher in the social sciences and physical sciences than in all other academic disciplines: theology, arts, sports, and linguistics.

These distinctions in departments may result from differences in the way academic programs are organized, both structurally and pedagogically. Science and social science courses, by the nature of their curriculum content, have an increased likelihood of open-ended assignment completion, longer project timelines, and more independent time for self-directed study conditions, which create a perfect storm of potential for students with low levels of self-regulation to take advantage of the lack of due dates and thus exacerbate procrastination behaviors. This conclusion aligns with research findings on the relationship between distance from a due date and how the structure of tasks may influence procrastination (Steel, 2007). In contrast, the arts, theology, and sports sciences have the possibility of having curricula that are more formally structured and based on performance or practice, which provide students with consistent feedback loops and therefore limit the opportunity for students to engage in avoidance behaviors because of uncertainty.

A significant practical implication is evident in the relationship between department and students' profiles, that is, the same risk profile does not lead to the same type or level of procrastination across all academic settings. This supports Touloupis and Campbell's (2024) research, demonstrating that the strength of the association between problematic social media use and academic procrastination depends on relevant academic context-related factors, and implies that strategies for interventions must consider both departmental curriculum and student-level psychological factors.

Age-Related Differences

A significant relationship existed between age groups and cluster profiles with respect to GAE ($F(2, 501) = 3.62, p < .05$). Students who were 23 years of age or older reported significantly higher GAE scores in the Digital Balanced-Success Oriented cluster as compared to those who were younger. This outcome indicates that the increased experience and academic maturity associated with students of this age group can lead to enhanced perceptions by students of their ability to achieve success. These perceptions are particularly pronounced in an environment where there is a positive self-regulated belief system.

This age-related development is supported by research showing that older university students will have higher levels of self-regulation than younger university students; therefore, older university students will have lower levels of digital addiction, as also found in the main effects of the current study. Older university students in early-to-mid adulthood from an Erikson's perspective would be at a stage of a more solidified sense of academic identity and goal orientedness, which reinforces beliefs of academic achievement and lessens the attraction of digital distraction as a method of avoiding academics. This is consistent with the developmental trajectory proposed by Kim et al. (2025), in which the presence of resources that serve as resilience resources to the effect of digital engagement on academic performance increases as one develops psychologically.

A particularly important finding in this study is the presence of an interaction between age and GAE, but not for DA or AP, which indicates a complex developmental pattern. For both digital addiction and procrastination, the age effect was consistent and negative, suggesting that as students get older, they tend to be less likely to engage in these behaviors, regardless of their profile membership status. However, the age effect on achievement expectancy was limited to students whose profiles indicated a digitally balanced and self-regulated academic orientation. Thus, in general, the effects of age on motivation are most pronounced for those with balanced profiles; however, age has little impact on the trajectory of students with risk profiles. The findings of this study have important implications for the development of prevention programs based on the early identification of risk factors. Specifically, students who exhibit a combination of high levels of digital addiction (DA) and low achievement expectancies (GAE) exhibit minimal changes in either behavior from ages 18 through 22. This suggests that the period when interventions would be most effective for students at risk of developing problematic academic habits is during the early years of undergraduate education.

Implications

The profile-based conclusions from this research have immediate implications for the planning of both preventative and intervention support programs at post-secondary educational institutions. Specifically, the identification of two profiles of students with different patterns of DA, AP, and GAE strongly suggests a move away from the use of "one size fits all" approaches to supporting the well-being of students and their academic success.

A three-part plan is suggested for students in the procrastinating-digital addict category. The first part involves teaching these students about their digital literacy and helping them understand how much time they spend on screens so they can become aware of and stop automatically using digital tools to avoid doing their schoolwork. These programs may be useful because research indicates that fear of missing out (FOMO) and a depletion of self-control are the two main processes by which digital activity leads to procrastination (Tang & He, 2025). The second area of support would involve providing cognitive-behavioral therapy (CBT) to assist these students in decreasing their unrealistically high performance standards and in decreasing catastrophizing when it comes to the possibility of failure; both of these areas would increase students' achievement expectancies, an identified psychological resource that is more prominent among non-risk than risk groups. The third area of support for the procrastinating-digital

addicts would involve structuring their learning environments with a variety of tools to compensate for their lack of self-regulation; one example of a tool could include breaking down a task into smaller parts, another could include giving students regular progress reports based on reaching specific milestones, and a final tool could be having students work together as peers to hold each other accountable for meeting deadlines and completing assignments. This structural support would likely be especially helpful in courses where students have open-ended projects or assignments.

For the Digital Balanced-Success Oriented student group, the primary focus will be on maintaining and reinforcing a motivational base to support academic success in light of the student's transition from lower-level to more demanding upper-division courses. To support this group of students through strength-based advising and academic identity development programs can help reinforce goal clarity and enhance self-efficacy beliefs, especially in times of high academic stress, which has the potential to lead to an increased reliance on technology.

In addition, the findings related to the students' age support that early-year screening assessments, such as brief assessment batteries that include items assessing both digital use and procrastination propensity along with achievement expectancy, may be particularly useful in identifying incoming students at risk for developing a procrastinating-digital addicted profile prior to the establishment of maladaptive behaviors. These assessments can be used as part of the initial screening process during new student orientation or during the first-semester advising.

Limitations and Future Directions

The cross-sectional design of this research does not allow for inferences about causality; therefore, it is not possible to determine whether the DA/AP/GAE relationships found in this research are bidirectional or unidirectional using only the data collected in this research. Longitudinal research (e.g., follow-up at different times during an individual's education) or experience sampling methodology (i.e., observing individuals as they go about their daily lives) would be required to assess changes in the academic profiles of students and to provide insights into the development of these profiles.

Second, the sample has a high percentage of females (78.7%) and is mostly comprised of social sciences students; this could impact the extent to which the study's results can be generalized to more representative or diverse university student populations. Studies have reported sex differences in both digital addiction and procrastination (Lin et al., 2025); therefore, further research should test whether the two-profile structure will replicate in samples with a more equal balance of males and females and/or across different countries and institutions.

Third, while hierarchical cluster analysis using Ward's method and Euclidean distance is a valid approach, it cannot generate probabilistic memberships for each profile or model fit indices in the same manner that latent profile analysis (LPA) can. Future studies may use LPA to validate the identified profile structures and to determine whether additional transitional sub-profiles (i.e., high DA but transitioning from high GAE) are present when larger sample sizes are used.

Finally, the three constructs used for clustering – DA, AP, and GAE – capture important aspects of the digital-academic risk landscape; however, they can not be entirely comprehensive. Future studies may incorporate other constructs, such as fear of failure, emotional regulation, and academic burnout. Each construct has been independently connected with both digital addiction and procrastination (Savaş et al., 2025; Rad et al., 2025). A person-centered approach that is sensitive to both co-occurring digital risks and motivational resources produces actionable results in this context, whereas variable-centered approaches cannot produce the same types of results because of their structure.

Declarations

Ethics Approval:

Ethical approval for this study was obtained from the Sakarya University Educational Research and Publication Ethics Committee (Approval Number: E-61923333-050.99-571740).

Conflict of Interest:

The authors declare that they have no relevant financial or non-financial interests to disclose.

Funding:

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Author Contribution

Conceptualization, Data collection, Writing-Original Draft- A.K., O.I., E.C.; Methodology, Analysis and/or interpretation- M.K.; Literature review, Introduction, Discussion and conclusion- A.K.,O.I., E.C., E.d.; Writing- Review & Editing- O.I., M.K.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

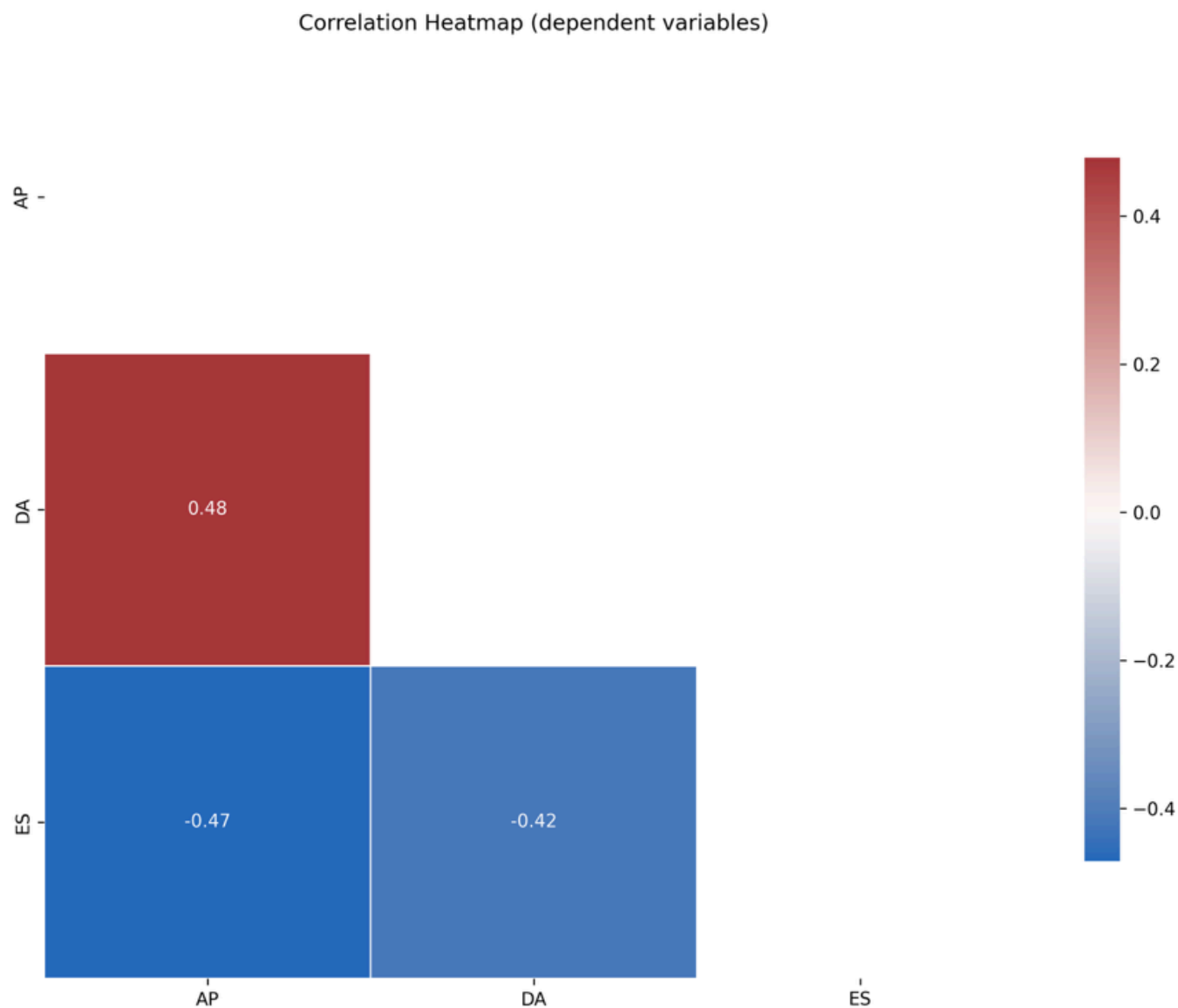


Figure 1

Correlation Heatmap

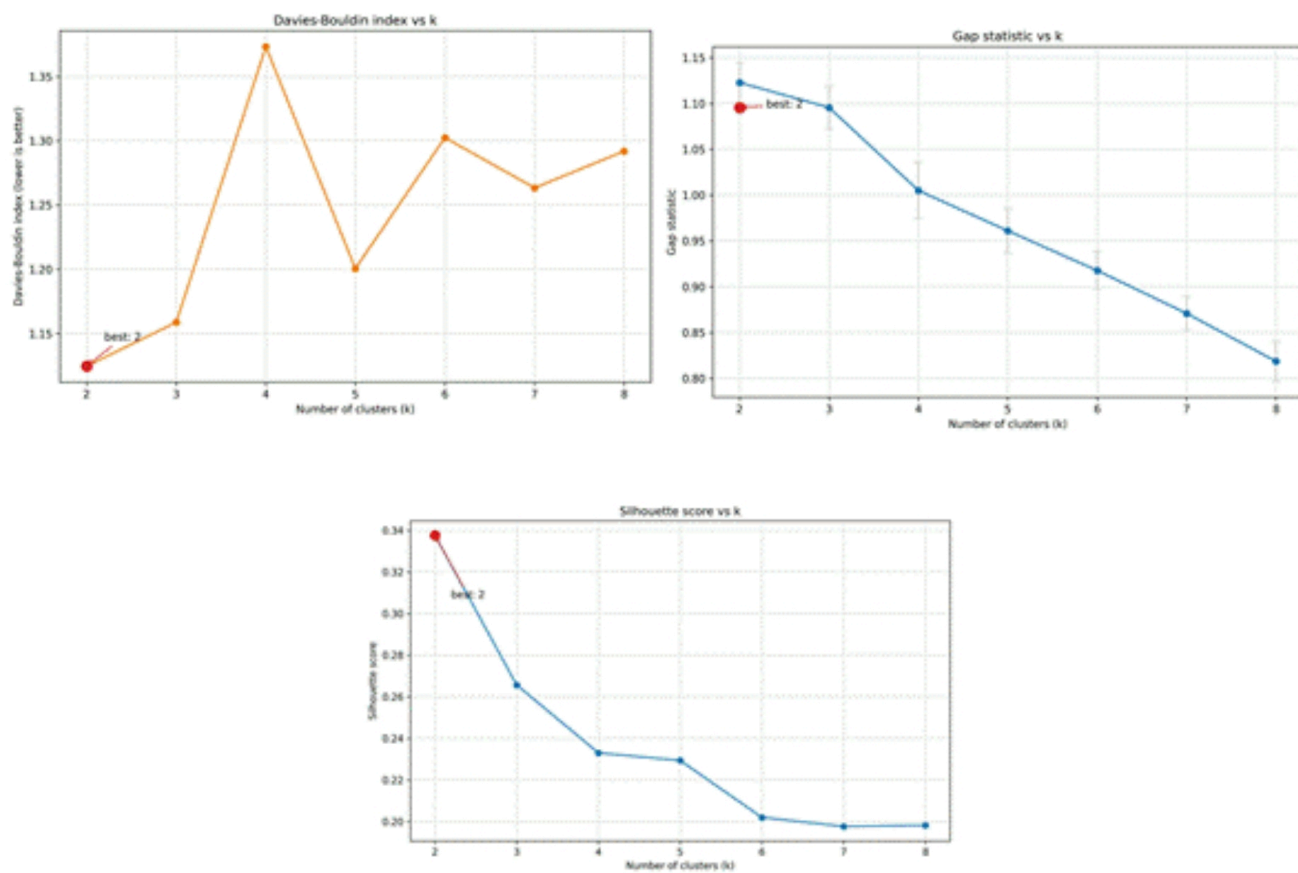


Figure 2

Validity Measures

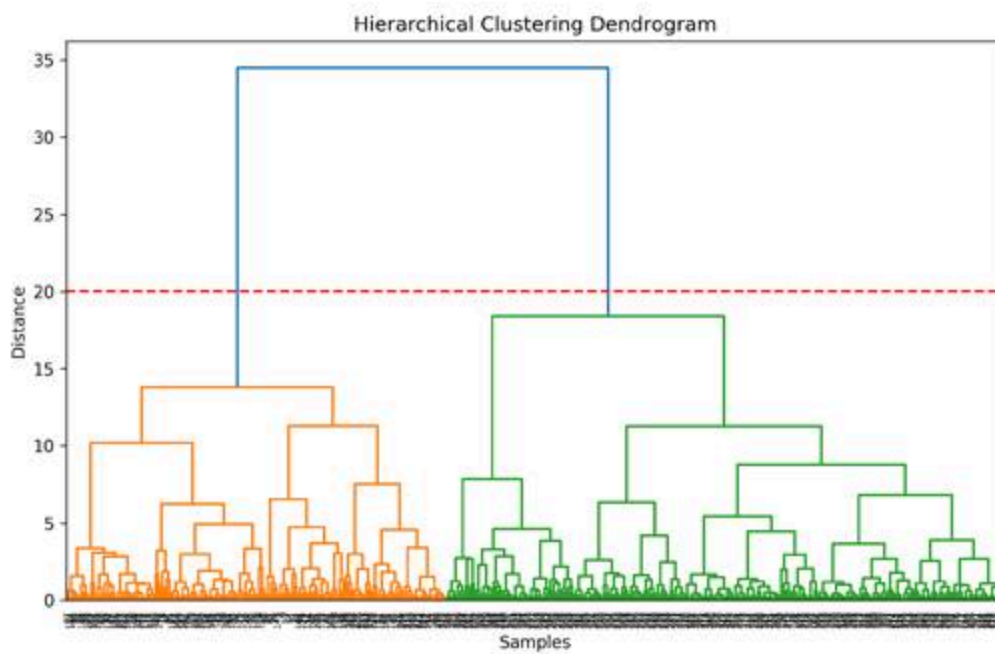


Figure 3

Hierarchical Cluster Dendrogram

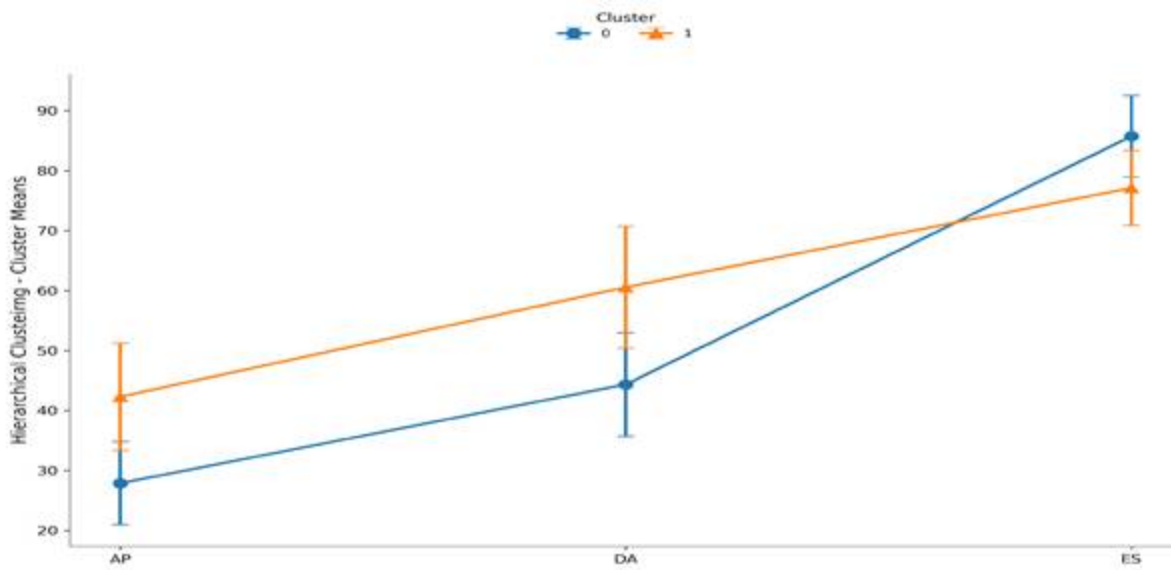


Figure 4

Hierarchical cluster analysis result