Motivating Item Annotations In Cultural Portals With UI/UX Based On Behavioral Economics

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***Abstract*—Digital repositories and cultural content delivery systems built on top of them are integral parts in the current form of cultural landscape. In these systems netizen engagement is paramount and it can take many forms ranging from participation to digital fora to custom multimedia creation. One important engagement manifestation is the annotation of cultural items stored in the portal. This allows the discovery of additional item aspects, properties, semantics, topical variations, and latent connections to other items and hence it is paramount in many technological and commercial levels. In order to ensure a sufficiently high level of netizen activity, UI/UX design guidelines based on behavioral economics principles can be integrated into digital repositories transforming the traditional one way interaction to a novel fully bidirectional experience and making thus netizens part of both the long term cultural preservation and the insight gain processes. This conference paper proposes a set of such guidelines along with best practices stemming from the worldwide use of digital repositories and cultural portals.**

***Index Terms*—behavioral economics, UI/UX, cultural content delivery, user annotations, cultural portals, digital repositories**

I. Introduction

The demand for cultural content as well as for creating large and reliable online cultural repositories is currently surging around the globe for a number of technological, finacial, and social reasons. The latter include fast and reliable computer networks capable of delivering multimedia with at least tolerable quality [1], easy worldwide access to diverse content [2], and the global rise of cultural awareness [3]. Cultural portals are among the principal mainstays supporting the infrastructure designed to cope with this increased demand. To this end, storing a large number of multimedia items and developing efficient analytics for content retrieval and recommendation are absolutely vital for their long term success.

Cultural portals can interact with their respective netizen base in a number of ways. To the latter may well belong short questionnaires, daily challenges, newsletters, glossaries and short introductions, media clips, online or real world competitions and giveaway prizes, or even small games, to name just a few of them. Such engagement can have diverse goals like data deduplication, latent aspect discovery, and item annotation. Behavioral economics is the field studying the various social, historical, psychological, and cognitive factors shaping human decision making [4] [5]. So far it has been successfully applied by various institutions to the effectiveness evaluation of the above strategies for their respective portals with positive measurable results [6].

The primary research objective of this work is a set of UI/UX design guidelines tailored for cultural content delivery portals and digital culture repositories. Specifically, the aim of these guidelines is to maintain a netizen engagement level so that not only a vibrant community is built around the portal, but also new non-trivial cultural item connections are discovered through manual annotations. These guidelines stem from established behavioral economics results as well as from best practice guides formulated by use cases around the globe.

The remainder of this conference paper is structural as follows. In section II the recent scientific literature regarding behavioral economics and cultural content delivery is briefly reviewed. Then in section III the principles relevant to this work are explained, while in section IV realistic guidelines are given along with assessment of respective alternatives. The main findings of this work as well as future research directions are described in section V. Technical acronyms are explained the first time they are encountered in the text. The term *netizen* used here refers to the users of the digital cultural repository, whether registered or visiting, whose engagement is sought after. Moreover, in the function definitions parameters always follow arguments after a semicolon. Boldface small letters denote vectors and ordinary small ones scalars. Finally, table I summarizes the notation of this work.

TABLE I
Notation of this conference paper.

Symbol	Meaning	First in
$\stackrel{\triangle}{=}$	Definition or equality by definition	Eq. (1)
$\{s_1, \ldots, s_n\}$	Set with elements $s_1, \ldots, s_n$	Eq. (1)
$\lvert\cdot\rvert$	Set cardinality functional	Sec. IV-A
$\mathrm{prob}\left\{\cdot\right\}$	Probability of an event occurring	Eq. (8)
$\lVert\cdot\rVert$	Vector or matrix norm as appropriate	Eq. (11)
$\hat{x}$	Estimator of quantity x	Eq. (7)

II. Previous Work

As stated earlier, the field of behavioral economics focuses on the factors involved in human decision making [7]. Current research topics in the field are explored among others in [8] and [9]. Exploring psychological pricing mechanisms and how they can be applied to changing established behavior patterns is the focus of [10]. The effects of bounded rationality can be found in decision making [5], in games for evaluating strategic decisions [11], and in organizational communication flow for crisis management [12]. Also, such considerations are inherent in the theory of computation as they help in understanding the difference in computing power between the classes of abstract computing devices [13] [14], for instance between a finite state automaton (FSA) and a pushdown automaton (PDA) [15].

Behavioral economics have numerous applications across a broad spectrum of fields, even in ones not directly related to finance or technology [16]. A meta-analysis indicates the success of applying behavioral economics for altering the demand characteristics for certain categories addictive commodities [17], clustering the netizen base of a cultural game [18], formulating educational principles to ensure student interest [19], and exploring the dynamics of currency unions [20]. Nudge theory has been applied to improving fairness in energy consumption [4] and regional and urban development [21]. Other concrete applications include social issues such as treating victims of cyberbullying [22], helping students concenrate on their respective coursework [23], increasing netizen enagement in portals [24], and assessing how portal content can be configured to drive it higher [25].

Digital culture and related content delivery systems have already reaped benefits from technological advances [26] [27]. Among them are similarity metrics for ontologies [28], automated construction of knolwdge graphs with natural language processing techniques (NLP) [29], advanced graphics [30], and sophisticated multimedia [31]. Over these portals can be set analytics for numerous functionalities such as computing the correlation coefficient between two static graphs or two realizations of random graphs [32], link prediction between multiascpect items [33], or the semantic enriched similarity metrics for cultural items [34].

III. Behavioral Principles

The results used here to derive the cultural portal recommendations are explained in this section. They describe human action patterns as well as the related conditions, exceptions, and limitations. In table II are shown the behavioral elements taken into consideration in this work.

Perhaps the most intuitive result in behavioral economics is that of *loss aversion*, namely the general tendency to take all possible measures to avoid losing something considered as valued or being on the wrong side in a conflict. Although this inclination may well be overriden by higher motives such as ideals or even rational thoughts, typically it is sufficiently strong to drive human options in a number of issues.

A related principle is that of the *perceived risk*, namely that humans use highly diverse and subjective assessments for risk. This includes the subjective evaluation of the same tangible loss. Therefore, even for a seemingly simple task such as manual item annotation possibly there is no single strategy for motivating netizens to do it successfully.

Rewards are the opposite of loss and typically humans tend to seek it both for tangible or intangible benefits but also for confirmation of their actions and choices. The *brain reward feedback loop* can learn to recognize such rewards and can drive a person to repeat a certain activity as long as they keep coming. However, this loop can be saturated depending on a number of factors including the relative value of rewards with respect to the associated loss or the reward predictability.

TABLE II
Behavioral elements and their applications.

Element	Effect	Role in
Loss aversion	Avoid or minimizing losses	Adaptive annotation Annotation window Annotation reward
Perceived loss	Loss is primarily subjective	Annotation reward Centroid visualization
Reward loop	Keep collecting rewards	Annotation window Speed maximization Centroid visualization
Default option	Trust authority or crowd	Adaptive annotation

The tendency to select the *default option* among multiple ones, especially when the perceived cost is similar across them, is another major finding. It states that most trust implicitly either authority, in case one created the available options, or the wisdom of the crowd, in case the default option was derived by statistical means or recommendation systems.

IV. Portal Recommendations

A. Item recommendations

Before describing the certain preliminary definitions are in order. Let Σ be the set of the cultural item categories for instance music, literature, theater, mythology as in (1).

$$\Sigma \triangleq \left\{\sigma_1, \ldots, \sigma_{|\Sigma|}\right\} \tag{1}$$

Then, $|\Sigma|$ is the total number of categories available in the portal. Depending on the underlying semantics of Σ, the items can belong to one or more of its categories.

Moreover, let V be the set of the cultural items stored in the portal as in equation (2) with $|V|$ being the number of items.

$$V \triangleq \left\{v_1, \ldots, v_{|V|}\right\} \tag{2}$$

Along a similar line of reasoning with the above, let L be the possible number of labels for the connections between the elements of V and $|L|$ the number of labels as in (3).

$$L \triangleq \left\{l_1, \ldots, l_{|L|}\right\} \tag{3}$$

One important metric which can be readily computed from the connectivity patterns between the cultural items and the portal categories is the density ρ_0 of equation (4). Let $e_{i,j}^k\left[t\right]$ be the indicator of an actual connection recorded as an annotation in the portal between the i-th category and the j-th item with the k-th label at discrete time point t. Then the ratio of the actual connections to their maximum possible number is defined as the density of the particular portal.

$$\rho_0\left[t\right] \triangleq \frac{\sum_{i=1}^{|\Sigma|}\sum_{j=1}^{|V|}\sum_{k=1}^{|L|} e_{i,j}^k\left[t\right]}{|\Sigma|\,|V|\,|L|} \tag{4}$$

Equation (4) is consistent with Metcalfe's law which states that the value of any network is a power law of the number of vertices, which is essentially a function of the number of edges [35] [36]. Recall that the latter are the primary vehicles of the network functionality. This is denoted by the denominator, where the maximum number of labeled links signifies a hard upper limit to the portal useability and hence of its value. This approach can also be found in other fields. For instance, in a social network context the number of connections between accounts is a metric of the underlying digital activity [37] [38], whereas in document databases such as MongoDB the links, typically denoting common authors or significant term co-occurences, between structured documents in various formats reveals latent similarities between them [39] [40].

The evolution of ρ_0 over time reflects the interest of the underlying netizen base in the cultural portal. The latter can be measured by the metric of equation (5):

$$\Delta\rho_0\left[t_2, t_1\right] \stackrel{\triangle}{=} \frac{\rho_0\left[t_2\right] - \rho_0\left[t_1\right]}{t_2 - t_1} \tag{5}$$

Equation (5) is the average slope of $\rho_0\left[t\right]$ and it is meaningful if and only if the discrete time points are equidistant. However, this does not exclude the option of monitoring portal density in different time scales for devising short- and long-term strategies. For a specific and constant time resolution h this change takes the form of equation (6):

$$\Delta\rho_0\left[t; h\right] \stackrel{\triangle}{=} \frac{\rho_0\left[t+h\right] - \rho_0\left[t\right]}{h} \tag{6}$$

Equation (6) can be considered as the speed the portal overall connectivity moves with in the space of possible link configurations. A robust portal can maintain a level of $\Delta\rho_0\left[t\right]$ for significant time periods, reaching its potential in a short amount of time because of the high netizen engagement. This leads directly to recommendation 1:

Recommendation 1 (Speed maximization): The overall portal UI/UX should be configured to attract and keep netizens in a way where its speed is maximized.

It should be noted that recommendation 1 is not simply a qualitative recommendation as there are computational tools and algorithmic predictors which can provide relatively accurate estimations on where density is moving, even in terms of local optimization. For instance, a linear predictor of length n can yield an estimate $\hat{\rho_0}\left[t\right]$ for the density at time t given its n past values as in equation (7), which is a linear finite impulse response (FIR) filter with coefficients $\{\beta_k\}$.

$$\hat{\rho_0}\left[t\right] \stackrel{\triangle}{=} \sum_{k=1}^{n} \beta_k \rho_0\left[t - kh\right] \tag{7}$$

The FIR coefficients can be computed with standard techniques such as the Yule-Walker and Wiener-Hopf equations or they can be adaptive with schemes such as the least mean squares (LMS) or the recursive least squares (RLS). Alernatively, accurate and computationally efficient estimators can be obtained from machine learning (ML) techniques such as regression or multilayer perceptrons (MLP).

Another behavioral principle can be derived about the latent knowledge obtained from clustering the items stored in the cultural portal. In order to discover latent patterns from the labeled links various clustering schemes are frequently used to derive representative items as well as extended classes based on the manual netizen annotations. Figure 1 shows a snapshot of a small scale repository with typical link structure. Specifically, these possible cases of connectivity patterns, one for each cultural category (represented by square vertices), are shown as described below:

- The dark gray (top) cateogry is characterized by a single and unique relationship connecting each item with the category. Under this scenario all items are treated uniformly through a functionality set highly dependent on the item nature. For example, there may be extensive capabilities for document similarity computation.
- The light grary (middle) category is another limiting case where there is a unique relationship for each distinct item. Frequently in this case, there is only a topical coherency between the items but otherwise they are very different. For instance, the items may pertain to the same historical event but they have distinct modalities.
- The white (bottom) category represents a general case where the corresponding items can be linked with different in the general case and possibly multiple ways with the category. This kind of relationships typically describe multimodal or multiaspect cultural items and have more potential for discovering latent knowledge.
- Another case similar to the above, not shown in figure 1 to avoid visual cluttering, is when items can belong to more than one categories. This fuzzy case can be addressed by suitable clustering algorithms and is often useful when cultural items in addition to being multimodal are multithematic or even crosscultural.

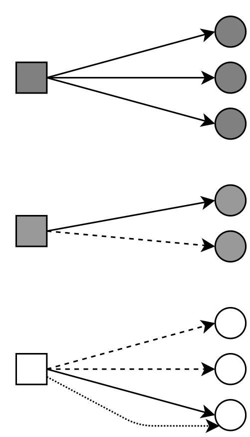

Fig. 1. Possible connectivity patterns (Source: Authors).

In the last case mentioned above the j-th item v_j may well belong simultaneously to more than one categories $\sigma_{i_1}, \ldots, \sigma_{i_m}$ with a different degree of participation $\mu_{i_k,j}$ and with various labels as appropriate. For instance, a certain myth may well belong to categories pertaining to mythology, sociology, theater, and lingustics and at the same time to have multiple versions. These factors essentially form a $|V| \times |\Sigma| \times |L|$ third order clustering tensor.

There are many ways to determine the participation degree of v_j to $\sigma_{i_1}, \ldots, \sigma_{i_m}$, which can be thought of as the *a priori* probability that v_j belongs to each of these categories. One is to consider that v_j belongs equally to them and hence:

$$\mu_{i_r,j} = \mathrm{prob}\{v_j \in \sigma_{i_r}\} = \frac{1}{m}, \qquad 1 \leq i_r \leq m \tag{8}$$

Alternatively, the pariticipation degree can be determined by the number of labeled links of v_j to σ_{i_r} to the total number of links to it as shown in equation (9):

$$\mu_{i_r,j} = \frac{\sum_k e^k_{i_r,j}}{\sum_k \sum_{r=1}^m e^k_{i_r,j}} \tag{9}$$

Given the available cultural categories any item can belong to, the weight w_{j_1,j_2} for any two v_{j_1} and v_{j_2} can act as a similarity measure between them. One possible way to define this weight is shown in equation (10), which can be thought of as a weighted Tanimoto similarity coefficient. In particular, the numerator is defined over the common categories $I_1 \cap I_2$ for v_{j_1} and v_{j_2}, whereas the denominator over their union $I_1 \cup I_2$.

$$w_{j_1,j_2} \stackrel{\triangle}{=} \frac{\sum_{i \in I_1 \cap I_2} (\mu_{i,j_1} + \mu_{i,j_2})}{\sum_{i \in I_1 \cup I_2} (\mu_{i,j_1} + \mu_{i,j_2})} \tag{10}$$

More advanced forms of equation (10) have been proposed in the recent relevant scientific literature.

Fuzzy clustering techniques can be used to discover item groups under connectivity restrictions typically expressed in terms of link coherency between items. Such techniques seek to minimize cost functions which in the general depend on the distances and similarities between items. A very common form of the objective cluster is shown in equation (11):

$$J \stackrel{\triangle}{=} \sum_{r=1}^{|C|} \sum_{j=1}^{|V|} w_{r,j} \left\| \mathbf{c}_r - \mathbf{v}_j \right\|_2 \tag{11}$$

In equation (11) the vector $\mathbf{v}_j$ represents v_j and contains attributes which depend heavily on the nature of the portal including netizen annotations. Moreover, $\mathbf{c}_r$ denotes the cluster centroid, which depends on the available items. The number of clusters is typically a hyperparameter optimized separately. The exact way of deriving the above centroids is a function of the operations allowed on the item vectors. Examples of this clustering include among others [41].

The difficulty of selecting the appropriate number of clusters has been proposed to be addressed with visualizing the proposed clusters and letting the netizens vote on the clustering quality. This allows fine tuning algorithms to take advantage of information provided directly by the netizen base. This leads directly to the following behavioral recommendation.

Recommendation 2 (Centroid visualization): The portal should benefit from visualizing cluster bounds and centroids in order to get feedback from netizens regarding the overall clustering quality.

In both recommendations 1 and 2 netizens can contribute to the overall portal performance by creating and annotating more links between items and categories or by evaluating clustering quality. These can be achieved only by proper and timely feedback from netizens. To this end and given the size of the underlying tasks, abiding by the behavioral principles described earlier can help obtain more and better results. Specifically, netizens should be rewarded for choosing the right clustering scheme in order for their reluctancy to contribute to be overcome. Perhaps these rewards can be proportional to be gain in the value of the objective function. Additionally, speed maximization can benefit from providing rewards proportional to the number of annotations given.

B. UI/UX recommendations

As shown earlier motives and incentives as well as their balance are crucial in generating and maintaining netizen engagement. In this subsection additional recommendations for the portal UI/UX design are given.

Since annotating the portal items can contribute to the portal quality, a gamified system of rewards can be in effect. To this end, recommendation 3 can be followed, which described a commonplace strategy among portals of various types. The elements of the abovementioned system may well include:

- **Points:** As netizens perform annotations, they collect points through a prespecified and open systems. The latter should be clear and easily understood with only a select few surprise components which motivate netizens to perform extra to find exactly these surprises.
- **Leaderboard:** The points collected by netizens are displayed in a publicly available and highly visible position. Besides the general leaderboard there may well be specialized or customized ones. They also act as incentives as above through netizen competition.
- **Badges:** Special achievements, portal events, or real world dates are signified by badges which may or may not be known in advance to netizens in order to maintain a positive element of surprise. As a rule they are visible and frequently part of the public netizen profile.

The above gamification building blocks may be functionally combined. This includes leaderboards of badges and special point packs coming with badges as an additional motive to collect them or participate to portal events such as completing a prespecified number of annotations, annotations of diverse types, or annotations for categories which lack links with items in comparison to the rest. The above are common practices across various portals and lead to recommendation 3.

Recommendation 3 (Annotation reward): The portal UI/UX should include a intangible reward system. If circumstances allow, these can be coupled with tangible rewards.

If the annotating scheme results in a low density speeds, then special annotation windows may be implemented by the portal administrators perhaps associated with unique badges. This can be also cast as an inducement prize, most frquently in the form of a competition. This observation is the basis for recommendation 4 shown below.

Recommendation 4 (Annotation window): A limited time window can boost portal annotations through standard gamification elements such as badges, inducement prizes, past successful annotations, and specialized point packs.

A final UI/UX design recommendation is that the portal analytics suite should be adaptive enough in order to understand the type of netizen using it in terms of loss and rewards. Therefore, the portal may tailor its reward offers in order to motivate netizens effectively. Figure 2 shows the high level behavioral architecture to achieve such an objective.

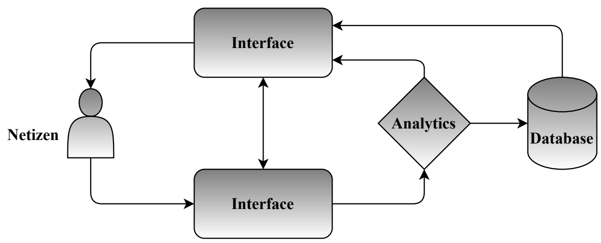

Fig. 2. High level architecture (Source: Authors).

The components of this system are the following. They primarily aim to facilitate netizens and let them express naturally, maximizing thus netizen input quality.

- **Input Interface**: The portal should be able to accept and efficiently recognize input in multiple formats such as text, voice commands, or even eye movement.
- **Output Interface**: It is integral in the communication of results and portal actions to netizens, especially if the item clusters are to be evaluated.
- **Analytics**: They constitute the heart of the adaptive capabilities portal. These may include graph mining, NLP, ML predictive, or clustering functionality.
- **Database**: It stores netizen profiles and clustering results in order to be used by netizens or by more advanced external meta-analytics. It can be relational or NoSQL.

The above can be summarized in recommendation 5.

Recommendation 5 (Adaptive annotation): The portal analytics should be able to adaptively discern a set of fundamental netizen types and tailor the reward system according to these types. Learning can be used to create netizen types or profiles.

The behavioral aspects of the above recommendations are as follows. Recommendation 3 takes advantage of the loss aversion and the perceived loss principles by overcoming them with the gamified reward system. Along a similar line of reasoning, recommendation 4 relies on the brain reward feedback loop to maintain acceptable levels of netizen engement. Moreover, recommendation 5 is based on these last principles but from a different perspective.

V. Conclusions And Future Work

The focus of this conference paper is the development of a novel set of UI/UX recommendations based on behavioral economics principles for ensuring a sufficiently high level of netizen activity in cultural content delivery systems and digital cultural repositories. Specifically, the objective is to motivate netizens to manually annotate various aspects of cultural items. Such annotations are expected to considerably increase the description quality of the stored items as well to significantly improve the performance of cultural analytics. As the latter rely heavily on the number and nature of connections, adding more through custom annotations coming from netizens with diverse viewpoints and backgrounds results in superior analytics performance in terms of a number of evaluation metrics.

The work presented here can be extended in a number of ways. Possible future research directions include the conduction of large scale experiments with real world datasets in order to evaluate the validity of the proposed design metrics. Moreover, advanced behavioral economics or neuroscience concepts can be used towards increased long term netizen engagement. Additionally, once actual UI/UX data are available from the systematic use of the digital repository, then personalized adaptive schemes based on feedback can be established taking into account the brain reward loop functionality.

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References

[1] I. Leyva-Mayorga, R. Torre, V. Pla, S. Pandi, G. T. Nguyen, J. Martinez-Bauset, and F. H. Fitzek, “Network-coded cooperation and multi-connectivity for massive content delivery,” *IEEE Access*, vol. 8, pp. 15 656–15 672, 2020.

[2] E. Kużelewska and M. Tomaszuk, “European human rights dimension of the online access to cultural heritage in times of the COVID-19 outbreak,” *International Journal for the Semiotics of Law - Revue internationale de Sémiotique juridique*, pp. 1–13, 2020.

[3] Z. Brzezinski, B. Scowcroft, and D. Ignatius, *America and the world: Conversations on the future of American foreign policy*. Basic Books, 2009.

[4] N. DellaValle and S. Sareen, “Nudging and boosting for equity? Towards a behavioural economics of energy justice,” *Energy Research & Social Science*, vol. 68, 2020.

[5] M. Cristofaro, “Herbert Simons bounded rationality: Its historical evolution in management and cross-fertilizing contribution,” *Journal of Management History*, 2017.

[6] K. Dowling, D. Guhl, D. Klapper, M. Spann, L. Stich, and N. Yegoryan, “Behavioral biases in marketing,” *Journal of the Academy of Marketing Science*, vol. 48, no. 3, pp. 449–477, 2020.

[7] V. Terziev and D. Kanev, “Modern developments in behavioral economics,” in *FarEastCon*. Springer, 2018, pp. 10–23.

[8] S. Wendel, *Designing for behavior change: Applying psychology and behavioral economics*. O’Reilly Media, 2020.

[9] A. Alvarez-Milán, R. Felix, P. A. Rauschnabel, and C. Hinsch, “Strategic customer engagement marketing: A decision making framework,” *Journal of Business Research*, vol. 92, pp. 61–70, 2018.

[10] M. Field, N. Heather, J. G. Murphy, T. Stafford, J. A. Tucker, and K. Witkiewitz, “Recovery from addiction: Behavioral economics and value-based decision making,” *Psychology of Addictive Behaviors*, vol. 34, no. 1, p. 182, 2020.

[11] K. Cooper, H. Schneider, and M. Waldman, “Limited rationality and the strategic environment: Further evidence from a pricing game,” *Journal of Behavioral and Experimental Economics*, vol. 90, 2021.

[12] A.-S. Claeys and W. T. Coombs, "Organizational crisis communication: Suboptimal crisis response selection decisions and behavioral economics," *Communication Theory*, vol. 30, no. 3, pp. 290–309, 2020.
[13] J. Bell, "Rationality in bargaining by finite automata," MSc Thesis, Wilfrid Laurier University. Theses and Dissertations (Comprehensive), 2019.
[14] X. Liu and J. Halpern, "Bounded rationality in Las Vegas: Probabilistic finite automata play multi-armed bandits," in *Conference on Uncertainty in Artificial Intelligence*. PMLR, 2020, pp. 1298–1307.
[15] A. Kučera and R. Mayr, "A generic framework for checking semantic equivalences between pushdown automata and finite-state automata," *Journal of Computer and System Sciences*, vol. 91, pp. 82–103, 2018.
[16] G. Drakopoulos, I. Giannoukou, P. Mylonas, and S. Sioutas, "The converging triangle of cultural content, cognitive science, and behavioral economics," in *MHDW*, ser. IFIP Advances in Information and Communication Technology, vol. 585. Springer, 2020, pp. 200–212.
[17] S. F. Acuff, M. Amlung, A. A. Dennhardt, J. MacKillop, and J. G. Murphy, "Experimental manipulations of behavioral economic demand for addictive commodities: A meta-analysis," *Addiction*, vol. 115, no. 5, pp. 817–831, 2020.
[18] G. Drakopoulos, Y. Voutos, and P. Mylonas, "Annotation-assisted clustering of player profiles in cultural games: A case for tensor analytics in Julia," *BDCC*, vol. 4, no. 4, 2020.
[19] A. S. Hayes, "The behavioral economics of Pierre Bourdieu," *Sociological Theory*, vol. 38, no. 1, pp. 16–35, 2020.
[20] A. Bertasiute, D. Massaro, and M. Weber, "The behavioral economics of currency unions: Economic integration and monetary policy," *Journal of Economic Dynamics and Control*, vol. 112, 2020.
[21] R. Huggins and P. Thompson, "The behavioural foundations of urban and regional development: Culture, psychology and agency," *Journal of Economic Geography*, vol. 19, no. 1, pp. 121–146, 2019.
[22] Y. Hayashi and N. Tahmasbi, "Decision-making process underlying bystanders helping cyberbullying victims: A behavioral economic analysis of role of social discounting," *Computers in human behavior*, vol. 104, 2020.
[23] B. Huang, K. F. Hew, and C. K. Lo, "Investigating the effects of gamification-enhanced flipped learning on undergraduate students behavioral and cognitive engagement," *Interactive Learning Environments*, vol. 27, no. 8, pp. 1106–1126, 2019.
[24] D. Liu, R. Santhanam, and J. Webster, "Toward meaningful engagement: A framework for design and research of gamified information systems," *MIS Quarterly*, vol. 41, no. 4, 2017.
[25] M. Schreiner, T. Fischer, and R. Riedl, "Impact of content characteristics and emotion on behavioral engagement in social media: Literature review and research agenda," *Electronic Commerce Research*, pp. 1–17, 2019.
[26] V. Miller, *Understanding digital culture*. SAGE, 2020.
[27] R. C. Smith, "Designing heritage for a digital culture," in *Design Anthropology*. Routledge, 2020, pp. 117–135.
[28] G. Drakopoulos, Y. Voutos, and P. Mylonas, "Recent advances on ontology similarity metrics: A survey," in *SEEDA-CECNSM*. IEEE, 2020.
[29] E. Marchand, M. Gagnon, and A. Zouaq, "Extraction of a knowledge graph from French cultural heritage documents," in *ADBIS, TPDL, and EDA 2020 Common Workshops and Doctoral Consortium*. Springer, 2020, pp. 23–35.
[30] C. Holtorf and A. Högberg, *Cultural heritage and the future*. Routledge, 2020.
[31] F. Salvo, M. DellOvo, D. Tavano, and L. Sdino, "Valuation approaches to assess the cultural heritage," in *International symposium: New Metropolitan Perspectives*. Springer, 2020, pp. 1746–1754.
[32] G. Drakopoulos and E. Kafeza, "One dimensional cross-correlation methods for deterministic and stochastic graph signals with a Twitter application in Julia," in *SEEDA-CECNSM*. IEEE, 2020.
[33] L. Manovich, *Cultural Analytics*. MIT Press, 2020.
[34] Y. Voutos, G. Drakopoulos, and P. Mylonas, "Metadata-enriched discovery of aspect similarities between cultural objects," in *SMAP*. IEEE, 2020.
[35] T. Peterson, "Metcalfe's law as a model for Bitcoin's value," *Alternative Investment Analyst Review*, vol. Q2, 2018.
[36] K. Alabi, "Digital blockchain networks appear to be following Metcalfes law," *Electronic Commerce Research and Applications*, vol. 24, pp. 23–29, 2017.
[37] Y. Li, Z. Su, J. Yang, and C. Gao, "Exploiting similarities of user friendship networks across social networks for user identification," *Information Sciences*, vol. 506, pp. 78–98, 2020.
[38] Q. Cao, H. Shen, J. Gao, B. Wei, and X. Cheng, "Popularity prediction on social platforms with coupled graph neural networks," in *International Conference on Web Search and Data Mining*, 2020, pp. 70–78.
[39] J. Cao, T. Wang, W. Li, and C. Tao, "A method of calculating the semantic similarity between English and Chinese concepts," in *International Conference on Machine Learning and Intelligent Communications*. Springer, 2019, pp. 313–324.
[40] T. I. Damaiyanti, A. Imawan, F. I. Indikawati, Y.-H. Choi, and J. Kwon, "A similarity query system for road traffic data based on a NoSQL document store," *Journal of Systems and Software*, vol. 127, pp. 28–51, 2017.
[41] G. Drakopoulos, I. Giannoukou, P. Mylonas, and S. Sioutas, "On tensor distances for self organizing maps: Clustering cognitive tasks," in *DEXA*, ser. Lecture Notes in Computer Science, vol. 12392. Springer, 2020, pp. 195–210.