Unraveling the Relationship between Content Design and Kinesthetic Learning on Communities of Practice Platforms

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Abstract

As a variant of the sharing economy, Communities of Practice (CoP) platforms have allowed kinesthetic learners to acquire skillsets corresponding to their interests for immediate or future use in practice. However, the impact of digital learning content design on kinesthetic learning remains underexplored in the field of information systems. We hence extend prior research by advancing content richness and structure clarity as antecedents affecting kinesthetic learners' digestibility of contents, culminating in differential kinesthetic learning effects. To substantiate our arguments, we collected data from a leading Chinese recipe sharing platform. Whereas content richness was measured in terms of readability, verb richness, and prototypicality, structure clarity was operationalized as block structure, block quantity, and block regularity. Employing a machine learning model, we simulated and tested learners' digestibility of image content embodied within recipes. Plans for future research beyond the current study are also discussed.

Keywords: Online Communities of Practice, kinesthetic learning, content richness, structure clarity

1. Introduction

Sharing economy platforms are experiencing unprecedented growth (Li et al., 2019; Melián-González et al., 2019; Puschmann & Alt, 2016). Through the provision of equal opportunities for users to exchange knowledge, Communities of Practice (CoP) platforms, as a variant of the sharing economy, differ from their traditional counterparts where knowledge sharing is primarily constrained to professionals (Eckhardt et al., 2019; Hu et al., 2019; Melián-González et al., 2019).

Focusing on practice and knowledge sharing, CoP platforms groups people who share a common interest or passion to acquire new skills and improve work practices, which in turn aids in knowledge creation and dissemination (Wubbels, 2007). A distinguishing characteristic of enculturation within CoP platforms is that of *learning to be*, which entails knowledge internalization through the rich context of social activity and practice within communities (Nichani & Hung, 2002). For example, one cannot become a doctor by merely reading about, or having discussions about, the practice (Nichani & Hung, 2002). In other words, unlike *learning about* which accentuates "knowing that" through the accumulation of factual knowledge (Brown & Duguid, 2017), *learning to be* is about "knowing how" via repeated application and practice.

CoP platforms have emerged as an enormous knowledge repository on which to base future practice (Gray, 2005; Schwen & Hara, 2003), carving out a space for online learning and professional skills acquisition. Yet, despite the availability of a vast assortment of online pedagogical materials to guide individuals' acquisition of new skills on CoP platforms, *learning to be* demands repeated application and practice (Gray, 2005; Luft & Buitrago, 2005) rather than mere browsing or finger-sliding, a mode of learning termed as *kinesthetic learning*.

Internalizing knowledge through repeating action sequences (Igbal et al., 2019), kinesthetic learning is instrumental to the acquisition of diverse skillsets such as cooking, dancing, and gymnastics. Kinesthetic learners attain knowledge through repetitive bodily movements to form muscle memory (Wood & Sereni-Massinger, 2016). Kinesthetic learners remember best what has been done and are distractible to long discourse (Syofyan & Siwi, 2018). These learners tend to develop a brain map of structured knowledge during learning to help them visualize specific steps or procedures and associate physical motions with given information (Igbal et al., 2019; Richards, 2019; Syofyan & Siwi, 2018).

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In contrast to offline kinesthetic learning which emphasizes interactive engagement between instructors and learners during the learning process (Wolfman & Bates, 2005), online learners oftentimes have to rely primarily on digital learning resources and learn through following instructions step-by-step (Fitter et al., 2018). For this reason, we argue that the design of digital content affects kinesthetic learners' digestibility of the latter, thereby culminating in dissimilar learning outcomes. To bolster the outcome of online kinesthetic learning, we attempt to offer an answer to the following research question: *how can instructional content be designed to promote kinesthetic learners' learning on CoP platforms*?

While extant literature has shown that digital content design affects students' learning (Cabot et al., 2014; Jeong & Yeo, 2014), it fails to elucidate the underlying mechanisms that lead to distinct effects. Additionally, even though studies on kinesthetic learning have increasingly stressed the matching of learning styles between instructors and students (Pritchard, 2017; Sek et al., 2015; Syofyan & Siwi, 2018), they lack adequate exploration of the impact of content design from the standpoint of information delivery. Furthermore, the effectiveness of standardized design norms requires further scrutiny to better regulate content sharing and encourage learners' engagement on CoP platforms (Danieau et al., 2013; Hyman et al., 2014).

The goal of this research is to overcome the preceding limitations by scrutinizing the impact of digital content design on learners' digestibility, thereby resulting in differential kinesthetic learning outcomes. We collected data from a leading Chinese recipe sharing platform to validate our hypothesized relationships. We delineate content design into its constituent sub-dimensions of content richness and structure clarity. Whereas content richness was extracted from recipe text based on Natural Language Processing techniques, structure clarity was calculated from both text and images contained in the recipe instructions. Learners' digestibility of a recipe was simulated and measured by a fine-tuned Convolutional Neural Networks model that automatically computes a human memorability score based on each image input. Learning effects of a recipe was observed from the number of peer cooking and comments for each recipe on the platform. All hypotheses concerning the relationship between content richness, structure clarity, digestibility, and learning effects were tested with PLS-SEM.

Empirical results demonstrate a positive relationship between learners' digestibility and their learning effects. There is a negative relationship between content richness and digestibility. The relationship between content richness and digestibility is positively moderated by structure clarity. Three aspects of this preliminary study are expected to contribute to the extant literature. Firstly, this study contributes to the dearth of literature on online learning content design by unpacking the relationship between digital content design and online learning effects. Secondly, we use cognitive load theory as the inherent explanation mechanism for the development of our key hypotheses, thereby operationalizing the cognitive load concept that is difficult to quantify. Lastly, using standardized content design on sharing economy platforms is beneficial for platforms' value creation and aligns with the mutual interests of platforms, learners, and content publishers.

2. Theoretical background

2.1. Content design and kinesthetic learning

Past studies have documented two content design factors affecting the effects of digital learning materials on learners: content richness and structure clarity (Britton et al., 1982). Scholars have contended that rich content-presentation types are positively associated with a high level of concentration, thereby bolstering the effects of online learning (Liu et al., 2009; Riding & Sadlersmith, 1992). In the same vein, structure clarity aids learners in constructing a coherent mental diagram of what the text means and organizing their memory for text-based content comprehension (Beasley & Waugh, 1996; Britton et al., 1982; Pyle et al., 2017).

A learning style is an individual's natural or habitual pattern of acquiring and processing information in learning situations (Smith & Dalton, 2005). According to learning style theories, individuals differ in the preference in which they acquire information (Wood & Sereni-Massinger, 2016). Kinesthetic learning is characterized by fast learning through physical activities that involve the whole body to process new and difficult information, rather than listening to lectures or watching demonstrations (Cuevas & Dawson, 2018; Igbal et al., 2019). Kinesthetic learners are good at recalling events and associating feelings or physical experiences with memory (Pritchard, 2017), but often find it difficult to keep still and pay attention to big chunks of information (Richards, 2019).

2.2. Cognitive load theory

Cognitive load theory focuses on the idea of efficient utilization of memory resources. *Cognitive load* refers to the load imposed on an individual's working memory by a specific learning task (e.g., problem solving, thinking, reasoning) (Schmeck et al., 2015). Learning more information than the memory can process or store at once will adversely affect the ability of the memory, thereby hindering learners' digestibility from absorbing knowledge (Busselle, 2017; Sweller et al., 1998). To enhance learners' ability to receive and digest information effectively, instructional materials should be designed to reduce the cognitive loads placed on their working memory (Boutyline & Soter, 2021).

Cognitive loads on learners' memory can be categorized into three types: *intrinsic cognitive load*, *extraneous cognitive load* and *germane cognitive load*. *Intrinsic load* refers to the level of complexity inherent to a specific instructional material (Sweller et al., 1998). *Extraneous load* pertains to elements added to the working memory which are unrelated, uncritical and unnecessary for the learning process (Ginns, 2006). In contrast, *germane load* refers to instructional features that promote the process of learning and facilitate the development of a learner's knowledge memory system (Paas et al., 2003).

3. Hypotheses development

3.1. Digestibility and learning effects

The content learning process of online kinesthetic learners can simply be divided into two key phases: learn and do. Learning process requires users to focus on the content and exert their mental energy to remember specific learning resources (Woods & Siponen, 2019), where cognitive load can be increased by distractions, such as unnecessary text, irrelevant images or heavy contents, which prohibit brain from processing and digest information simultaneously (Jenkins et al., 2014). When the cognitive load exceeds learners' mental capacity and limitations (the working memory has a limited capacity to process information), it causes information overload and impedes their digestibility of new knowledge, therefore impairing learning effects (Woods & Siponen, 2019). In short, in the context of online learning, the more memorable and impressive the digital content is, the more likely it is to foster learning effects.

For instance, regardless of the difficulty of a lesson (intrinsic load), breaking heavy contents into small chunks or bite-sized information is usually a good practice to provide learners with more memory space to remember new information (Kirschner et al., 2006), thus allowing crucial content to be more easily retained in the brain and recalled for later use. Furthermore, the use of redundant artificially induced information (high extraneous load) can impair learners' retention, therefore, reducing unnecessary or unrelated information can help learners focus on key ideas and absorb information more effectively (Skulmowski & Rey, 2020). In addition, bolding keywords and color-coding information (high germane load) have a greater impact on learners' knowledge memory systems than normal ones (Paas et al., 2003), which enhance future recall and digestion. Thus, we propose that:

Hypothesis 1: Digestibility of the learning material is positively related with learners' learning effects.

3.2. Content richness, structure clarity and digestibility

During the online learning process of kinesthetic learners, they tend to practice by mental simulation to develop a certain knowledge schema or structure in their brain, which leads to comparable performance improvement in cognitive levels that promote digestibility and further influence ultimate learning effects (Kirsh, 2013; Riding & Douglas, 1993; Riding & Sadlersmith, 1992). Cognitive levels, associated with efficient structured retention of information in the context of digital learning, are primarily determined by textual and visual information, such as textual descriptions, product images, and video demonstrations (Jiang & Benbasat, 2007). Therefore, to improve kinesthetic learners' comprehension and digestibility, learning resources are supposed to be designed to match their distinct learning characteristics such as stimulating their mental simulation of practice (Igbal et al., 2019; Meehan-Andrews, 2009; Richards, 2019; Syofyan & Siwi, 2018).

For example, since kinesthetic learners prefer to engage in activities by experiencing and doing things instead of reading tedious and obscure learning materials, making learning content easily readable and understandable seems a sound way to increase digestibility and promote greater participation (Çakiroğlu et al., 2020). Moreover, kinesthetic learners may find it difficult to follow steps and procedures if they cannot envision themselves executing them (Apipah et al., 2018). Therefore, the frequent use of verbs can assist learners in visualizing specific steps and procedures, exemplify specific associated physical motions with given information and eventually facilitate their digestibility. Moreover, introducing some novelty into learning materials can hold the learners' interest and help them become more concentrated on the content to better digest it (Cuevas & Dawson, 2018; Syofyan & Siwi, 2018). Therefore, we hypothesize:

Hypothesis 2: Content richness underlying in the learning material is positively related with learners' digestibility of the material such that richer content brings about enhanced digestibility.

Structure clarity, on the other hand, will intuitively and heuristically work in concert with content richness to some degree to enhance or mitigate the cognitive load placed upon learners' memories. Earlier research has suggested that diagrams and pictures that closely illustrate the content of text can reduce extraneous load and increase germane load imposed on learners' memory and further assist in their comprehension and digestion of new knowledge (Levie & Lentz, 1982; Mayer, 1989). Besides, kinesthetic learners can often have difficulty staying focused on a particular lengthy learning task (Wells, 2012). Therefore, partitioning contents into multiple parts is a general best practice in a digital learning environment to manually lower the intrinsic load of learning materials and facilitate learners' digestibility (Sargent et al., 2011). Furthermore, relatively small text variation between different content chunks makes the learning resources look regular and patterned at first glance, thus simplifying learners' perceived intrinsic load, promoting engagement and benefitting digestibility of these information blocks (Pyle et al., 2017; Wulf et al., 2010). Therefore, we propose:

Hypothesis 3: Structure clarity strengthens the relationship between content richness and digestibility such that easy-distinguished structure facilitates digestibility.

Considering the above discussion regarding content richness, structure clarity, digestibility and learning effects, we develop the following conceptual framework, which incorporates all the hypotheses and constructs mentioned previously, as shown in Figure 1.

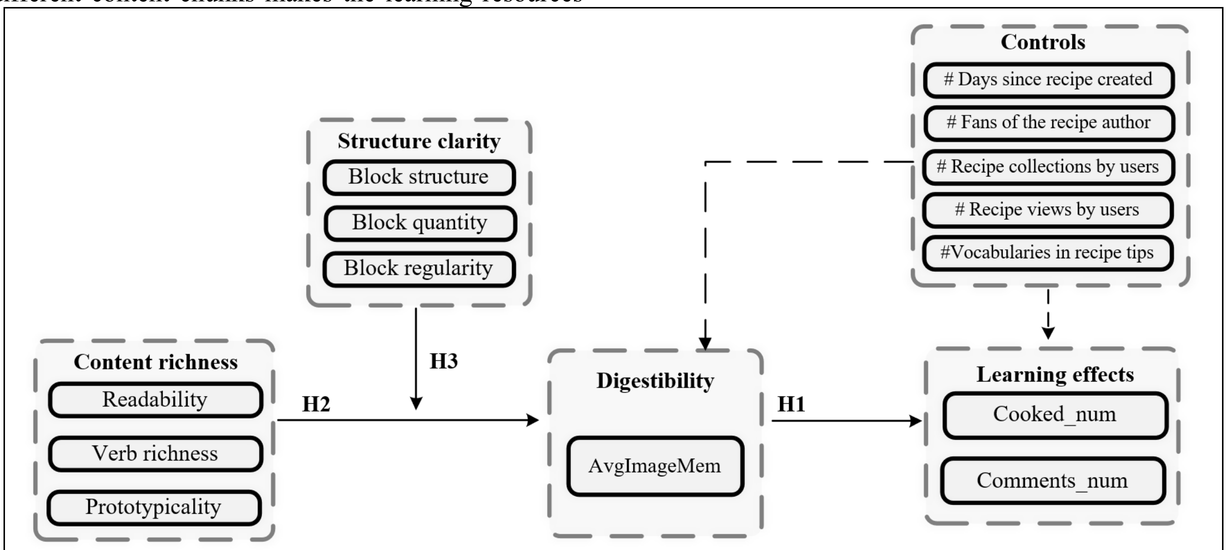

Figure 1. Research Model

4. Empirical Analysis

4.1. Data collection

To validate our proposed research model, data was collected from a leading Chinese recipe sharing platform with more than one million monthly active users. Cooking is a typical representative of kinesthetic learning because it requires the whole-body involvement of learners to acquire a recipe. It is on this platform that a large number of gourmet enthusiasts share their recipes to attract fans and attention. These food lovers are thus developing and publishing personalized recipe content in a variety of styles, which serves as a natural form of testing our hypotheses. To reduce the possible recipe category bias (e.g. fruit recipes versus meat recipes), the platform-provided "fruit" category was singly chosen out as the unique category for our recipe collection, under which there are the largest number of recipes compared with other recipe categories.

Initially, altogether 961 recipes in Chinese within the fruit category were collected, with each recipe having five main components, namely, the title (including the title text and cover image, e.g. "Orange satisfaction [steamed egg with orange], unlock new fruit eating method"), recipe description (e.g. "There was a whole box of navel oranges in the house. I couldn't finish it. I used them as food by the little cook"), ingredients (e.g. "Oranges (4), eggs (4)"), instructions (e.g. "Wash the oranges and cut about 1/4 of the bottom to serve as a lid") and tips (e.g. "Sugar water can be boiled by yourself or you can search for fructose on Taobao.").

The ultimate dataset contains the basic information of 961 recipes and 684 authors' profile information such as the total number of followers (or fans) and the number of recipes collected by the users on the platform.

The earliest created recipe was in June 2011 and the most recent was in September 2021. The number of fans one author owns ranges from 1 to 1,240,000.

4.2. Operationalization of focal variables

Measurement was developed based on indicators commonly used in content design. Firstly, content richness contains three formative indicators which are readability, verb richness and prototypicality respectively. Readability reflects the average reading difficulty level of a recipe. It is assumed that users are more likely to choose those better readable recipes to cook at their quick first sight. Based on the work of (Qiu et al., 2018), readability is calculated out of 18 linguistic features based on Chinese characters. Verb richness is extracted by word segmentation to show the number of unique verbs in a recipe (Apipah et al., 2018). For online kinesthetic learning, the use of verbs embodies the accuracy and diversification of describing specific instructional actions and at the same time avoids counting nouns that already appear in the ingredients list where proper nouns contribute little to the content richness. Prototypicality examines to what degree the content contained in one recipe is unique to its rivals (other recipes in the same recipe category) (Johnson et al., 2015). It represents the originality of a recipe and can be obtained from text cosine similarity (Reimers & Gurevych, 2019). The assumption is that if a recipe is more distinct from other recipes in the same category, it is easier to understand and retain.

Second, the construct structure clarity is formatively measured by block structure (Hargreaves, 2005), block quantity (Sargent et al., 2011) and block regularity (Pyle et al., 2017; Wulf et al., 2010), all of which can be calculated through images and text in the instruction block of a recipe. Block structure reflects the proportion of images and text within a recipe. A more balanced block structure (e.g., a reasonable ratio of images to text) is expected to present a clear structure view for kinesthetic learners to follow, probably facilitating better digestion of given information. Block quantity reflects the average complexity of a recipe. Kinesthetic learners may find it harder to acquire recipes with too many steps. Block regularity implies the neatness of recipe structure. It may influence learners' initial intention to learn a recipe, since kinesthetic learners do not expect big chunks to show up.

Third, digestibility is extracted from a machine learning technique that objectively measures human memory from images (Khosla et al., 2015). The image method uses fine-tuned deep Convolutional Neural Networks to estimate the memorability of images from many different classes, which provides a concrete means to perform image memorability manipulation. Digestibility is thus represented by the average memorability score of images from each recipes' instruction blocks.

Finally, we also include the peer cooking and comments number of a recipe as the formatively representative to reflect users' learning effects. Both variables indicate learners' actual participation and evaluation of using the recipe for finishing cooking after their reading. In addition, some control variables are directly obtained from either recipe content or the author's home page. Construct definitions and operationalizations are displayed in Table 1.

Table 1. Definition and Operationalization of Focal Constructs

Construct	Definition & Operationalization	Formula
Note: We assume there are C categories of recipes altogether. In category i, there are N_i (i = 1,2, …, C) recipes in total. For the specific i^{th} category, recipe j (j=1,2, …, N_i) has overall M_{ij} steps in its instruction block, P_{ij} images and V_{ij} vocabularies in its content.		
Content richness		
Readability (Qiu et al., 2018)	Readability measures how easy a piece of text is to read. It is a key factor in user experience. Readable content builds trust with your audience. This indicator reflects the average reading difficulty level of a recipe. The less readable the text is, the more difficult it would be, but likely higher content richness. It is calculated based on total Chinese words in each instruction step of the recipe's instruction block.	$readability_{ij} = \frac{1}{M_{ij}} \sum_{k=1}^{M_{ij}} block\_readability_{ijk}$ where i=1,2, …, C; j=1,2, …, N_i. $readability_i$ is the readability of the j^{th} recipe of category i^{th}, $block\_readability_{ijk}$ is the readability of kth step of the j^{th} recipe of category i^{th}.
Verb richness (Apipah et al., 2018)	Verb richness is the plentiful use of verbs in a recipe. More abundant use of verbs is likely to help kinesthetic learners visualize specific steps or procedures to better digest a recipe. This indicator reflects the average verb richness in a recipe. The more verbs used, the richer the content is. It is	$verb\_richness_{ij} = \frac{1}{M_{ij}} \sum_{k=1}^{M_{ij}} block\_verb\_richness_{ijk}$ where i=1,2, …, C; j=1,2, …, N_i.

	calculated based on the number of unique verbs in each instruction step of the recipe's instruction block.	
Prototypicality (Johnson et al., 2015)	Prototypicality reflects the distinctiveness of a recipe compared to its counterparts. The more prototypical, the richer content a recipe shows. The prototypicality of a recipe is calculated based on the average cosine similarity of recipe-to-recipe text. In this paper, we only consider the text from instruction block when calculating prototypicality.	$prototypicality_{ij} = 1 \Big/ \sum_{k=1,k\neq j}^{N_i} \frac{text\_cosine\_similarity_{ijk}}{N_i - 1}$ where i=1,2, …, C; j=1,2, …, N_i.
Structure clarity		
Block structure (Hargreaves, 2005)	Block structure reflects the proportion of images and text within a recipe. It is based on the ratio of the number of images to vocabularies in the instruction block of the recipe.	$Block\_structure_{ij} = \frac{Images_{ij}}{Vocabularies_{ij}}$ where i=1,2, …, C; j=1,2, …, N_i.
Block quantity (Sargent et al., 2011)	Block quantity reflects the number of different chunks in instruction block. It is based on the total number of steps in the instruction block of a recipe.	$Block\_quantity_{ij} = M_{ij}$ where i=1,2, …, C; j=1,2, …, N_i.
Block regularity (Pyle et al., 2017; Wulf et al., 2010)	Block regularity reflects the pattern consistency between different blocks. It is based on the standard deviation of vocabularies between each step in the instruction block of the recipe.	$Block\_regularity_{ij} = vocabularies\_std_{ij}$ where i=1,2, …, C; j=1,2, …, N_i.
Digestibility		
AvgImageMem (Khosla et al., 2015)	AvgImageMem refers to average memorability score of all images in the instruction blocks of a recipe. The machine learning algorithm reaches a rank correlation of 0.64, near human consistency (0.68).	$\text{AvgImageMem} = \frac{1}{P_{ij}} \sum_{k=1}^{P_{ij}} AIM_k$ where i=1,2, …, C; j=1,2, …, N_i; AIM_k is the memorability of kth image in the instruction blocks.
Learning effects		
Cooked_num	Cooked number indicates how many users cooked one recipe after learning it. It is calculated by the peer finished cooked number of the recipe.	Directly collected from the recipe page
Comments_num	Comments number indicates the degree of which a recipe is discussed. It is calculated by the peer comments number of the recipe.	Directly collected from the recipe page

4.3. Measurement model

Descriptive statistics for each focal variable are shown in Table 2. To validate our hypotheses, we employ Partial Least Square (PLS) with the plssem package provided by Stata17.0. Discriminant validity was evaluated by contrasting the ratio of the between-trait correlations to the within-trait correlations using the Heterotrait-Monotrait Ratio (HTMT) of correlations (Henseler et al., 2015). After the discriminant validity assessment, HTMT values of all focal variables used in our model were lower than the recommended threshold of 0.85 (Henseler et al., 2015). It showed that latent variables could be distinguished, suggesting a good discriminant validity.

Construct reliability and validity of latent variables were evaluated by Conbach's alpha (α) coefficient, composite reliability and AVE. Since all the latent variables in our model were formatively measured by manifest variables, these three reliability and validity indicators were equal to one. Besides, VIF values for all variables were less than 2, which indicated that collinearity did not cause a severe issue in the dataset.

Table 2. Descriptive Statistics

Variable	Mean	Min	Max	Std
Content richness				
Readability	0.56	-39.27	15.72	2.70
Verb richness	4.73	0.00	45.00	3.77
Prototypicality	1.75	1.44	5.27	0.29
Structure clarity				
Block structure	0.08	0.00	0.49	0.05
Block quantity	11.45	1.00	108.00	8.87

Block regularity	8.98	0.00	90.04	8.35
Digestibility				
AvgImageMem	0.86	0.77	0.89	0.03
Learning effects				
Cooked_num	638.52	0.00	4387.00	1186.61
Comments_num	147.02	0.00	909.00	246.48
Controls (# represents "the number of")				
# Days since the recipe created	903.13	104.056	3848.369	939.61
# Recipe author's fans	82451.74	1.000	1243172.00	213248.40
# Recipe collections by users	28601.84	5.000	530000.00	55581.27
# Recipe views by users	334607.46	211.000	8330000.00	706492.82
# Vocabularies in recipe tips	47.14	0.000	1039.00	87.15

4.4. Hypotheses testing

The path coefficients and hypotheses test results of our proposed research model are shown in Table 3. Analytical results are displayed as follows.

First, as expected, it is found that digestibility of the learning material is positively related with learning effects (β_1 = 0.035, p = 0.015). Understandably, the more digestive the learning material is, the more easily for kinesthetic learners to recall it for later use after their learning stage. In turn, lower digestibility in learning process invisibly increases cognitive load consequently impairing learning effects. Therefore, hypothesis H1 is supported.

Second, there exists a significant negative relationship between content richness and digestibility (β_2 = -0.213, p = 0.000). However, as opposed to the expected positive relationship proposed in H2, it shows a negative coefficient otherwise, indicating that learners' digestibility decreases with the increasing content richness. It is likely that, although a certain amount of content richness is expected to increase comprehension and digestibility of kinesthetic learners, too much content can be regarded as an extra burden for learners that can also adversely affect the digestibility of learning content. Therefore, hypothesis H2 is not supported.

Third, structure clarity shown in the learning material positively moderates learners' digestibility on the material in a significant positive way (β_3 = 0.114, p = 0.048), which means when the content richness is similar, a more transparent structure tends to help learners better digest the presented information. Therefore, hypothesis H3 is supported.

Table 2 Results of Hypotheses Testing

Hypothesis	Construct Relationship	Path Coefficients	p-values	Results
H1	digestibility → learning effects	**0.035 (β_1)**	**0.015***	**Supported**
H2	content richness → digestibility	**-0.213 (β_2)**	**0.000*****	**Not supported**
H3	content richness*structure clarity → digestibility	**0.114 (β_3)**	**0.048***	**Supported**

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Discussion and future plan

As a typical representative of sharing economy, CoP platforms are promoting the learning and practice of professional skills. However, the use of normalized design norms in presenting digital learning content on these platforms has not yet been explored. Unlike traditional offline kinesthetic learning, which impresses learning by doing, online learners usually have to rely on digital learning resources to learn a skill, making digital learning content design especially pertinent on CoP platforms since the quality of content design directly affects online learning effects. On the one hand, content richness is related with learners' extent of cognitive load which further influences their ultimate learning effects. On the other hand, structure clarity is also associated with helping learners in forming a connected, arranged and organized mental diagram to reduce cognitive load and thus facilitate final learning effects. Although extant literature has shown that digital content design affects learning effects, they fail to elucidate the underlying mechanisms that result in different effects. We extend previous research by advancing content richness and structure clarity as antecedents influencing kinesthetic learners' digestibility of contents, culminating in differential kinesthetic learning effects. Empirical results show that learners' digestibility is positively related to learners' learning effects. Content richness underlying learning material is negatively associated with learners' digestibility on the material. Structure clarity shown in the learning material positively moderates learners' digestibility.

Our study aims to contribute to the extant literature in two folds. Firstly, this study unpacks the relationship between digital content design and online learning effects, especially addressing the role of content richness and structure clarity in influencing learning effects via the key mediating path of digestibility, thereby enriching the relative dearth of literature on online learning content design. Our study provides empirical support to the positive role of digestibility in improving learning effects, the negative role of content richness in influencing digestibility and the positive role of structure clarity in moderating the relationship between content richness and digestibility, furthermore advancing the current study on effective design of digital content under specific sharing economy platforms (Cristobal-Fransi et al., 2019; Sutherland & Jarrahi, 2018). Secondly, we use cognitive load theory as the inherent explanation mechanism to develop the key hypotheses on the relationships of content richness, structure clarity, digestibility and learning effects under specific kinesthetic learning context, therefore operationalizing the cognitive load concept which is difficult to measure. Cognitive load theory is thus extended to understand how to benefit online learning effects from the standpoint of content design and information delivery in sharing economy context. The operationalizable constructs we developed can also serve as effective references for other online learning scenarios or knowledge sharing platforms. To our best understanding, this is a timely work that introduces cognitive load theory into sharing economy context to help us better understand and promote online learning effects (Abramova et al., 2017; Wang et al., 2014).

The application of standardized content design to CoP platforms is also crucial for regulating content sharers and encouraging greater user participation, which is beneficial for platforms' value creation and coincides with the mutual interests of platforms, learners and content publishers (Camilleri & Neuhofer, 2017). As for platforms, increased income produced by more participants is their primary motive. Access to rich, structured content can lead to better learning effects, resulting in a more active user base which in turn contributes to an increased amount of knowledge exchange. CoP platforms desire high activity levels, which usually entails additional revenues from ad revenues and additional product sales. Increased activity can also result in a more vibrant sharing economy community, benefiting the CoP platforms themselves as an additional bonus. In terms of learners, standardized content management not only contributes to better learning outcomes, but also saves them time spent on learning materials of low quality to focus on high-quality learning resources. Furthermore, it becomes easier for publishers of content to attract more fans and develop greater social capital by promoting their released content.

Our study indicates that both digital content richness and structure clarity presented on CoP platforms can significantly influence kinesthetic learning effects by influencing learners' digestibility of new knowledge. We have currently collected relevant data regarding recipes and authors, and the construct measurement and variable operational methods are presented. We will proceed with the future plan primarily on three fronts. First, we will conduct more robustness checks to substantiate our proposed model. During the process, we will also carefully reexamine the relationship between kinesthetic learning scenarios, research model and hypotheses development, to better contextualize all the distinct elements under kinesthetic learning. Second, we will try to find out the possible reasons why Hypothesis 2 fails to be supported in the primary empirical analysis. Although a certain amount of content richness is expected to increase learners' digestibility as hypothesized above, too heavy content on the other hand can be estimated to negatively affect digestibility as well. Therefore, we will also check whether there exists a quadratic effect between content richness and digestibility in our further empirical analysis. Third, more measurement methods will also be developed and adjusted to better operationalize each construct. Particularly, more unique components that reflect the special kinesthetic learning content are to be considered both in the main research model and in the robustness checks. Besides, alternative objective indicators that measures digestibility are to be identified and integrated into our model to better capture learners' degree of digestibility of learning material.

It should also be noted that our current work has some limitations. A first limitation of our study is that we did not account for individuals who might have cooked with a recipe, but did not indicate that they had done so or leave comments on the page. Our results may be affected by these users. Second, the popularity of recipes could affect the results of this study as well. For example, people for the most part may dominantly choose one specific fruit recipe over other types, which could further bias the estimation.

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