International Journal of Information Management 68 (2023) 102595

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Research Article

A twin data-driven approach for user-experience based design innovation

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ARTICLE INFO

Keywords:
User experience
Data-driven
Product design
Design innovation
Requirement analysis

ABSTRACT

Data-driven innovation has received increasing attention, which explores big data technologies to gain more insights and advantages for product design. In user experience (UX) based design innovation, user-generated data and archived design documents are two valuable resources for various design activities such as identifying opportunities and generating design ideas. However, these two resources are usually isolated in different systems. Additionally, design information typically represented based on functional aspects is limited for UX-oriented design. To facilitate experience-oriented design activities, we propose a twin data-driven approach to integrate UX data and archived design documents. In particular, we aim to extract UX concepts from product reviews and design concepts from patents respectively and to discover associations between the extracted concepts. First, a UX-integrated design information representation model is proposed to associate capabilities with key elements of UX at the concept, category, and aspect levels of information. Based on this model, a twin data-driven approach is developed to bridge experience information and design information. It contains three steps: experience aspect identification using an attention-based LSTM (Long short-term memory) network, design information categorization based on topic clustering using BERT (Bidirectional Encoder Representations from Transformers) and LAD (Latent Dirichlet allocation) model, and experience needs and design information integration by leveraging word embedding techniques to measure concept similarity. A case study using healthcare-related experience and design information has demonstrated the feasibility and effectiveness of this approach.

1. Introduction

With the fast development of modern information and communication technologies (ICT) such as social media and various websites, designers and companies can acquire and gain value from large and heterogeneous data, such as online customer reviews, feedback and patent documents (Bresciani et al., 2021; Kushwaha et al., 2021). They are valuable data sources for various design activities, such as strategic planning, design innovation, and concept generation (Liu et al., 2020).

In past decades, user experience (UX) has become a critical factor in product and service design (Zhou et al., 2022). UX reflects a user's preferences, product features or functions involved, and interaction between the user and the product or service in different contexts and various aspects (ISO-DIS-, 9241–210, 2010). As technologies improve and customer experiences evolve, consumer-products companies are undergoing time-to-market pressure and severe market competition. To maintain a competitive edge in the rival market, the first essential process is to identify opportunities such as perceived needs and newly discovered technologies (Karl Ulrich & Maria, 2020). To create a superior user experience (UX), designers have to identify the market's needs and design concepts from a UX perspective to enhance consumers' satisfaction. In this context, it requires exploring heterogeneous data and synthesising data from internal and external data sources, mainly including UX information and design information, for UX-based design innovation.

To better support design activities, the capture, representation, and archiving of UX and design information play a vital role in conceptual design. To understand UX in various application scenarios, some studies focus on the multidimensional constructs of UX (Verhoef et al., 2009), such as behavioural, affective, and social responses, while others emphasize the influencing factors (Hassenzahl & Tractinsky, 2006), including use environment, product features, and user emotions when interacting with a product. Most previous studies adopt interviews and customer activities and use surveys or questionnaires to capture UX needs, which are often labour-intensive. In our previous research, we studied from a data-driven perspective to leverage large online customer

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https://doi.org/10.1016/j.ijinfomgt.2022.102595
Received 4 September 2022; Received in revised form 27 October 2022; Accepted 5 November 2022
Available online 14 November 2022

reviews to identify influencing factors of UX (Yang et al., 2019) and integrated hedonic quality and pragmatic quality (Tong et al., 2022) to better interpret UX. Meanwhile, regarding the representation and archiving of design information, the conventional approaches are typically centred on structuring function-related design information (Hu et al., 2022). For example, user needs are translated into functional-related statements and design information is represented in functional aspects, such as function and behaviour, and structural aspects, such as component and solution (Liu L, 2020; Wang R, 2018).

However, UX information from external resources and design information from internal resources are often isolated in different systems. In addition, most of the design information is represented and archived based on function-related aspects but not from a UX perspective. In this context, designers have to manually search for meaningful UX-related design concepts from massive data. Moreover, it shows that about 80% of the digital information is in textual format (Shi et al., 2017). Its complexity, volume, and variety make the UX information extraction and design concept association process time-consuming and laborious for designers. Therefore, the effective exploration of innovation potentials from big UX and design data requires designing a systematic and feasible approach to building connections between UX and design information representations and facilitating the search for UX-oriented design information.

In this context, to help designers' idea generation in UX-based design innovation, particular to facilitate the exploration of UX data and design data, we aim to extract concepts from these two data sources and discover meaningful concept connections from textual data. We propose a twin data-driven approach to associate UX requirements obtained from the online product reviews with possible capabilities from the documented internal design information. In particular, the proposed approach exploits machine learning and text mining techniques to extract UX information, categorize design information and integrate these two kinds of data sources based on semantic connections. Our approach can suggest highly associated technological capabilities with UX needs as potential concepts for UX-based design innovation. Our study contributes to the relevant research in three ways as follows:

- A UX-integrated design information representation model is first introduced for UX-based design, in which we propose associating UX needs with design information using ontology to integrate UX with possible capabilities.
- A twin data-driven approach is designed to computationally and systematically integrate UX requirements extracted from the online product reviews with possible capabilities from the textual internal design information.
- We conduct case studies on online product reviews and patents to demonstrate the feasibility of our approach.

The remaining sections are organized as follows. Section 2 surveys related work about UX information and knowledge management for conceptual design. Section 3 proposes our UX-integrated design information representation model. Based on this model, in Section 4, a twin data-driven approach for bridging UX and design information is proposed. In Section 5, a case study of smartphone design is presented to demonstrate how our approach can facilitate idea generation for UX-based design innovation. Section 6 discusses some relevant studies and Section 7 concludes.

2. Related work

Recently, several studies on big data, artificial intelligence, and meta-analysis have been investigated for supporting data-driven innovation, management, and decision-making (Duan et al., 2019; Dwivedi et al., 2021; Jeyaraj & Dwivedi, 2020). In this study, we investigate the literature on UX analysis and design information for conceptual design to identify the research opportunities we can offer for UX-based design innovation.

2.1. UX analysis

With the recent advances in mobile and computing technologies, UX is gaining increasing attention in marketing, product and service design, and development (Becker & Jaakkola, 2020). It is becoming a critical point of competitive differentiation, which drives product/service innovation and business planning (Keiningham et al., 2020). To understand UX requirements for product design, researchers have studied how UX needs can be collected, represented, and analyzed to meet their academic and application goals.

The concept of UX has been investigated from different perspectives. Some studies take a subjective and holistic view of UX, where the entire interaction process in a specific context is considered, rather than a single task (Lemon & Verhoef, 2016; Patrício et al., 2011). In the context of the product-service system, Schallehn et al. (2019) evaluated UX in three stages, including before, during, and after the purchase of the offering. To empower smart product service, Bu et al. (2021) captured UX physiological signals to assess users' mental state and feedback towards the interaction with the product. Several other studies have explored the constructs of pleasant experiences. Hassenzahl et al. (2010) suggested evaluating UX from need fulfilment, hedonic and pragmatic quality of the interaction. Kujala et al. (2011) analyzed UX from other viewpoints, such as ease of use, attractiveness, and utility. To interpret UX, some research has focused on the influencing factors of experiences. In the design of subway station ecosystems, Zhou et al. (2012) considered experience factors such as environmental settings, other users, and social attributes and products. Most of these studies apply survey-based methods, which usually use questionnaires or self-reports to collect UX-related data to analyze users' subjective responses to products. The survey process is often time-consuming and labour-intensive.

With the popularity of social media, user-generated data such as online product reviews and comments, which contain users' concerns and expectations of the product, is acknowledged as invaluable information for product design and marketing (Dwivedi et al., 2022; Jin et al., 2019). Two significant research topics of using online product reviews are users' requirement analysis (Bi et al., 2019; Wang et al., 2019) and comparative advantages analysis of various products (Chang & Lee, 2018; Jin et al., 2016). Both the users' needs and the comparative analysis can inspire designers to search, identify and generate optimal design concepts, and help the company in product planning. For example, customer satisfaction dimensions were extracted from online reviews and their effects are measured (Bi et al., 2019). Product usage context, which is one of the factors affecting product design, consumer behaviour, and consumer satisfaction, was identified and clustered from product reviews (Suryadi & Kim, 2019). In addition, to associate customers' needs with engineering tasks, the customer reviews were translated into engineering characteristics for quality function deployment (Jin et al., 2015).

More recently, data-driven approaches have become an emerging topic in UX research. Some researchers have attempted to collect and extract UX information from online user-generated content such as online product reviews and reports using computational approaches. Yang et al. (2019) extracted important UX factors, such as usage situation, product features, and users' feelings, from online product reviews. By clustering the factors, the extracted information helps designers understand the significate usage context and features. To further analyze the UX elements, Tong et al. (2022) classified users' feelings in terms of hedonic quality and pragmatic quality using Natural Language Processing (NLP) techniques, such as word sematic and synonym. Some other researchers investigate using data mining techniques to support decision-making in UX design. Chien et al. (2016) considered UX attributes, such as users' background, perception, and UX reactions for notebook visual aesthetics design. After collecting the data using questionnaires, they generated rules to capture the relationship between aesthetic features and UX reaction. Lin (2018) focused on smart production in the glass recycling circular economy. He used sensor and Internet of Things technologies to collect user behaviour data and applied a decision-making system to identify the key product features and crucial user characteristics.

2.2. Design information for conceptual design

In addition to understanding user needs, generating creative ideas and design concepts, determining feasible techniques, and so forth are the main activities in the conceptual design process (Karl Ulrich & Maria, 2020). To support these knowledge-intensive design activities, various design information, such as design specifications, design know-how, and relevant technology, is needed. This information can be obtained from external resources, such as online patents and journals, and internal resources, such as design reports, and engineers' log books.

To support the archiving, retrieval, and reuse of design information, design information modelling, including its structure and accessibility, has been studied over the past few decades. Most of the studies deal with design information from a functional aspect (Li et al., 2017; Liu L, 2020; Umeda et al., 1996). For example, Li et al. (2017) designed a patent classification method based on the functional basis where they regarded product functions as innovation attributes. Liu et al. (2020) provided a retrieval tool for cross-domain patents from a functional basis by applying a semi-supervised learning algorithm. Komoto & Tomiyama (2012) studied a computer-aided conceptual design framework that focused on hierarchical decomposition and supported multiple product descriptions from functional, structural, parameter, and behavioural aspects. To support bio-inspired design, Chen et al. (2021) studied a structure-function knowledge method to represent and extract biological design information. In addition, some research focuses on the rationale aspect of design information to help designers in understanding why the artefacts are designed this way. One of the early rational models is the Issue-based Information System (IBIS), which uses issues, positions, arguments, and their relationships to express design knowledge (Rittel, 1970). To facilitate the archiving of rationale information, Liang et al. (2012) designed a computational approach using text mining to discover design rationale from design documents based on their ISAL (issue, solution, and artefact layer) model.

In terms of the design information, the representation methods can be summarized into three different approaches, including logic-based representation, matrix-based representation, and graph-based representation (Wang R, 2018). In the logic-based representation, concepts and explicit relationships are described using first-order logic, description logic, production rule, and so forth (Witherell et al., 2010). Matrix-based representations typically use similarity and relationships to represent connections between objects and features (Huang et al., 2017), which are commonly used in identifying product specifications in product design. Compared with the former two representations, graph-based representations are widely studied as they can show concepts or entities and their complex relations. Their typical applications include semantic networks, ontology, concept maps, and knowledge graphs (Han et al., 2021). Some studies use graphical modelling tools to capture design knowledge while this process usually requires significant human involvement. For example, Chang et al. (2008) developed a graphical tool with ontology and a database to capture design knowledge and help to locate proper information given a query. Some recent studies explore text mining and NLP techniques to facilitate the construction of the design knowledge graphs from a large number of textual design documents. For example, Zhang et al. (2017) studied a graph-based framework to support knowledge reuse in new product development, where ontology-based knowledge maps and knowledge navigation were involved. Siddharth et al. (2021) attempted to build an engineering knowledge graph by extracting entities and their relationships from claims of patents based on the defined syntactic and lexical rules.

In summary, the design information is usually represented in terms of function and structure to support product design and development in traditional conceptual design. However, for the design based on user experience, this design information is often isolated from UX requirement analysis, and cannot meet designers' information needs centred on UX. Furthermore, few studies have addressed the association of design information and UX aspects to facilitate conceptual design for design innovation. Therefore, to better support experience-oriented design, it is desired to have a systematic approach to establish the connection between user needs and possible capabilities, such as technological and design capabilities.

3. UX-integrated design information (DI) representation model

Since both UX information and design information are useful in UX-based conceptual design, it is necessary to have an information representation model which can provide hierarchies and concept-level semantic relationships to integrate information from the two data sources, i.e., UX information and design information. Furthermore, since we are in the era of big data, where incremental data is generated, this representation method should be able to handle large-scale, evolving, and machine-readable information (Wang Z, 2018). In addition, it should be empowered with artificial intelligence (AI) capabilities to better utilize the latest technologies in text mining, machine learning, and NLP. Based on these considerations, we propose a UX-integrated information representation model to combine these two heterogeneous kinds of information to support UX-based product innovation.

Fig. 1 shows the proposed representation model, which utilizes our previous UX modelling (Tong et al., 2022; Yang et al., 2019) and design rationale modelling (Liang et al., 2012) for UX and design information respectively, and a semantic-based method to link relevant information at three diverse levels, including aspects, categories, and concepts. In this model, the UX information consists of four aspects: product, situation, UX interaction/experience state, and user cognitive aspects. The product aspect represents product characteristics that involve several categories, such as features, services, and functions. The situation describes the contextual factors of using a product, which can be divided into different categories, such as time, activities, and places. The UX interaction/experience state refers to users' feelings towards the experience. It can be described in several categories: sentiment, hedonic quality, and pragmatic quality. The user cognitive aspect is about user-related information, which can be categorized into user groups (e.g., experienced users and novices), and user background. Fig. 2(a) shows examples of smartphone UX from online product reviews.

The design information is represented from a rational perspective, including motivation, solution, and artefact aspects. The motivations describe the objectives and reasons for designing a product. They can be divided into several categories: design problem, limitation of previous design, opportunity, and aim. The solution aspect describes how the motivations can be addressed and fulfilled. It can be summarized from the categories such as approach, service, technology, design ideas, and considerations and arguments for introducing an approach. The artefact aspect refers to the structure or function of a product design. Fig. 2(b) shows examples of smartphone design information from patent documents.

To construct connections between the two heterogeneous information, two information levels of relations are considered, including category-level and concept-level. The category-level connections refer to hierarchies of the same data source. As described above, each aspect can be further classified into several categories based on the topic similarity. In each category, the information can be further clustered into various groups based on semantic similarity. The concept-level connections are used to associate concepts between UX and design information not only based on the concept similarity but also the semantic similarity of their language context. By leveraging different information levels, the information integration can help unveil the underlying associations between

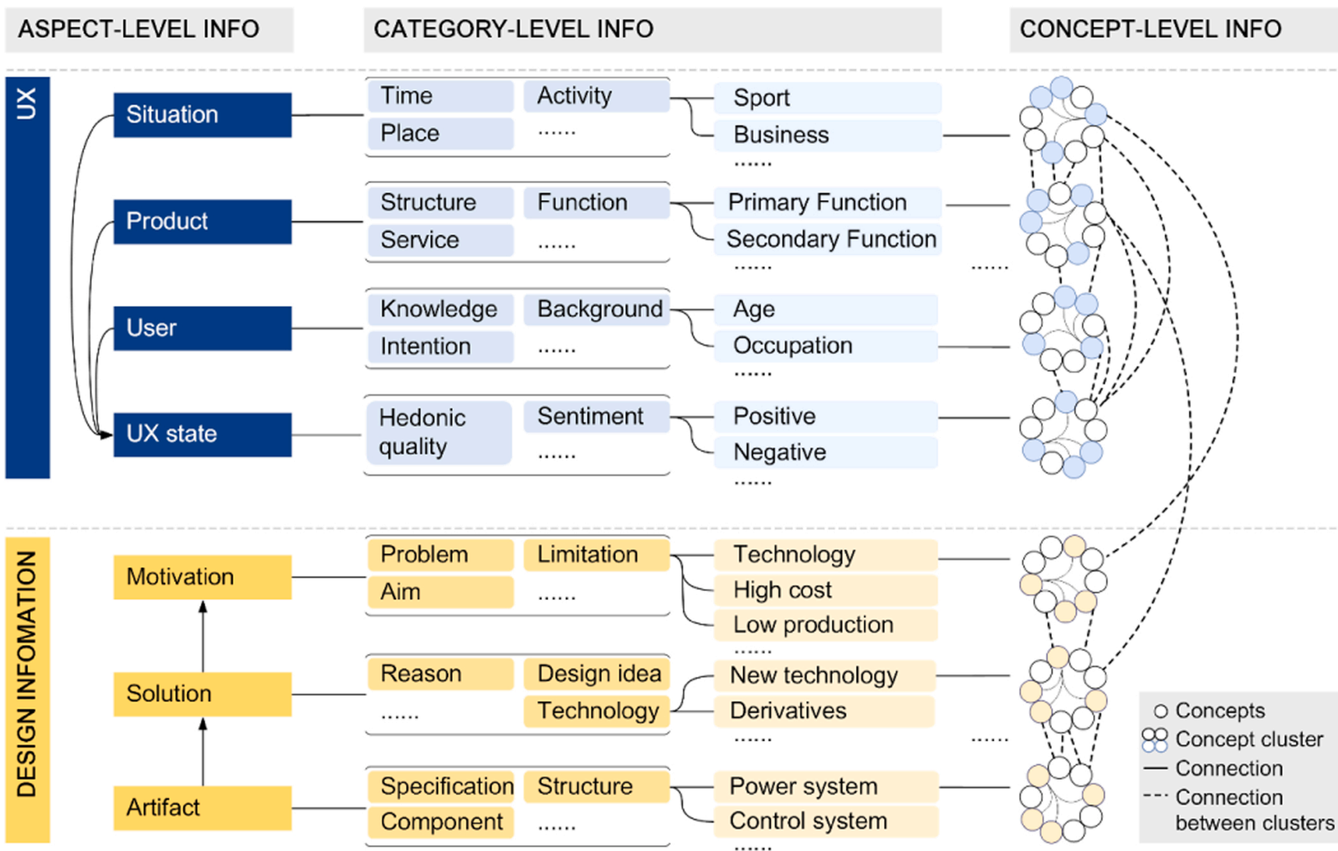

Fig. 1. The proposed UX-integrated information representation model for UX-based design.

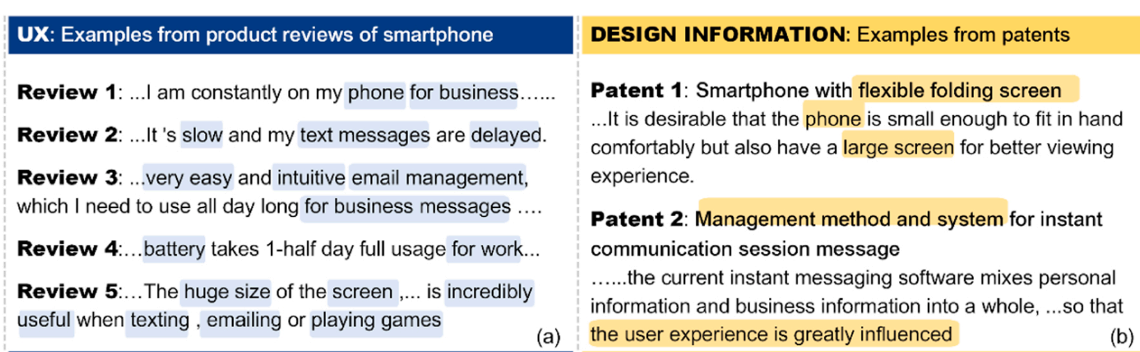

Fig. 2. Smartphone UX and design information Examples.

concepts, categories, and facets of UX and design information to support design idea generation. Using the UX and design data examples shown in Fig. 2, Fig. 3 illustrates a UX-integrated information representation for smartphone design using "screen" and "business" as associated concepts.

4. A twin data-driven approach for bridging UX and design information

4.1. Framework

Based on the UX-integrated information representation model, we propose a twin data-driven approach to combine the UX and design information from two data sources using text mining, machine learning, and NLP technology. This approach consists of UX data processing, design data processing, and UX and design information integration, as shown in Fig. 4. The first two data processes transform text from a free-form format to meaningful information at the concept, category, and aspect levels. The integration process reveals the association between these two sources of information by combining them according to their semantic context.

The UX data were crawled from online product reviews. The UX data processing is to uncover concept and category information of product, situation, and UX state aspects from textual UX data through processes of identification and clustering. Firstly, the UX recognition method is designed to extract UX-related information from sentences of the UX data. This extraction converts the free text into a structured format. Then a UX clustering method is developed to categorize the isolated UX information into semantic groups. This clustering helps aggregate the UX information scatted across different reviews into category-level information. Furthermore, to obtain a quantitative view of the clustered information, a UX quantification method is explored to measure the importance of the category. The weighting of the importance indicates

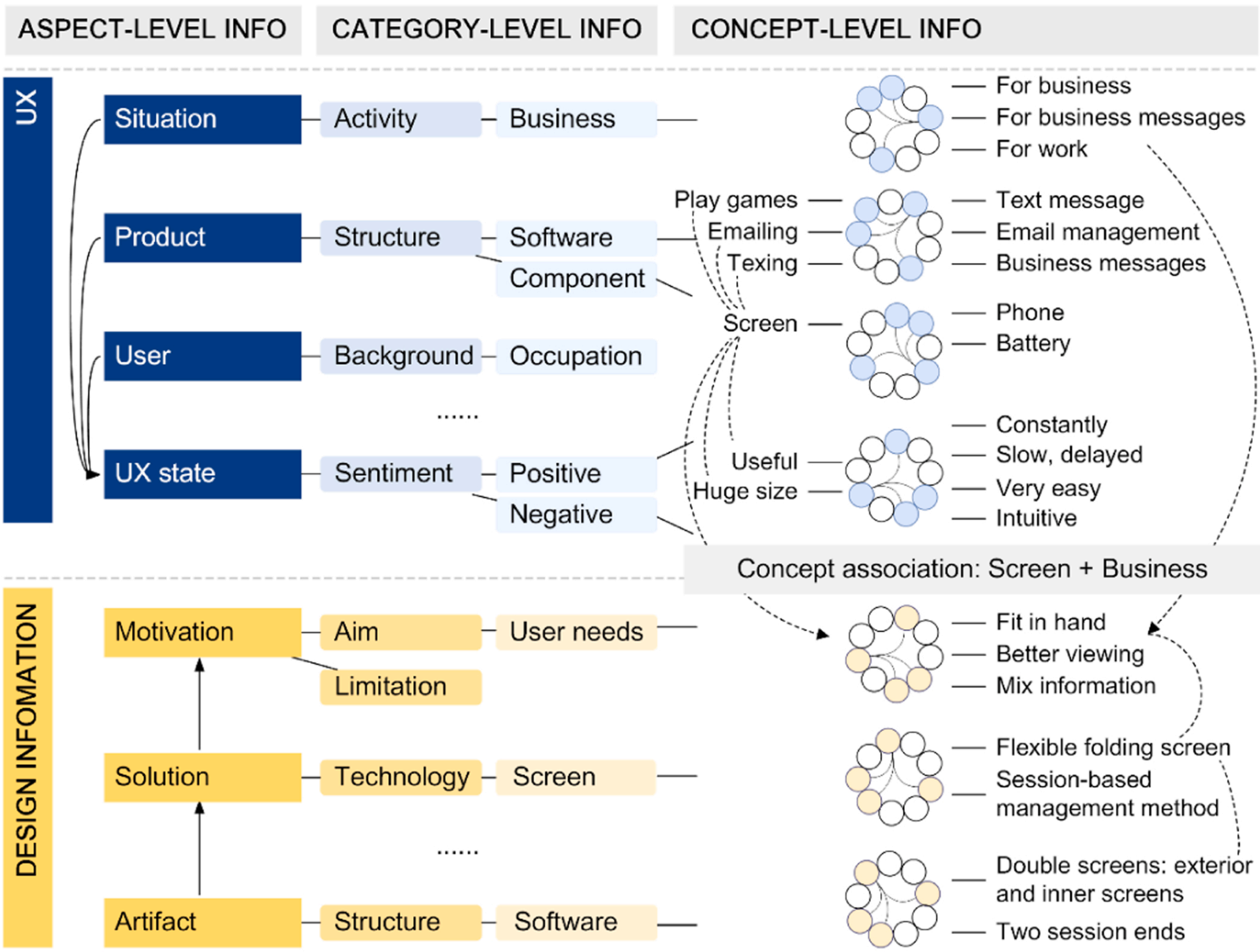

Fig. 3. An illustration of UX-integrated information representation for smartphone design.

the priority of UX needs.

The design data can be retrieved from archived design documents regarding design reports, patent documents, specifications, etc. In this study, we focus on the most common textual format and use patent documents as examples because they contain rich design information. The design data processing aims to unveil design-related concepts, topics, and design information networks to better understand the design information. Firstly, an aspect identification method is designed to extract concepts related to motivation, solution, and artefact aspects of design information. The concepts can be represented in various forms, such as sentences, phrases, and terms. Then a design information clustering method is developed to group concepts based on their topics in terms of these three aspects. Moreover, by measuring the distance between concepts, a design information network is constructed to link up relevant concepts.

To combine these two data sources for product design and innovation, a UX and design information integration process is proposed. In this process, a semantic concept representation method is designed to represent concepts using information embedding. Then a semantic association is to combine similar concepts of these two sources based on their semantic relationships. Building up the connection between these two sources can help designers to prioritize the UX needs and identify their corresponding associated design concepts.

4.2. Identifying and weighting aspects from UX information

Over the past two decades, regarding sentiment analysis of product reviews, researchers have analyzed textual reviews at different information levels, such as review summarization to gain overall opinions (Liu et al., 2017) and product feature level opinions (Ding et al., 2009), for different applications. In this paper, we further conduct fine-grained sentiment analysis to increase the interpretability of product reviews for UX analysis. In our previous studies, we proposed the task of UX modelling, where we extracted each piece of UX information from a review sentence (Tong et al., 2022; Tong et al., 2022). There are four aspects including user, product feature, situation and an expression about the user's state. The UX information in each sentence indicates that the user expressed how they felt about the product feature when using the product feature in a certain situation. It implicitly defines the relationships between the aspects of UX information.

The UX recognition process is firstly designed to form the tuple from each review sentence based on our previous study (Tong et al., 2022). It is considered a supervised sequence labelling task, where each token of a sentence is labelled with an IOB (Inside, Outside, Beginning) scheme tag of a UX aspect. In this labelling, to encode the text as word vector representation, we use the BERT (Bidirectional Encoder Representations from Transformers) model (Devlin et al., 2019) since it has been widely used in NLP tasks (Koroteev, 2021). On top of it, a CRF (Conditional random field) layer is used to form a token-level classifier to predict the tag for each token (Liu M, 2020). Based on each labelled token, the

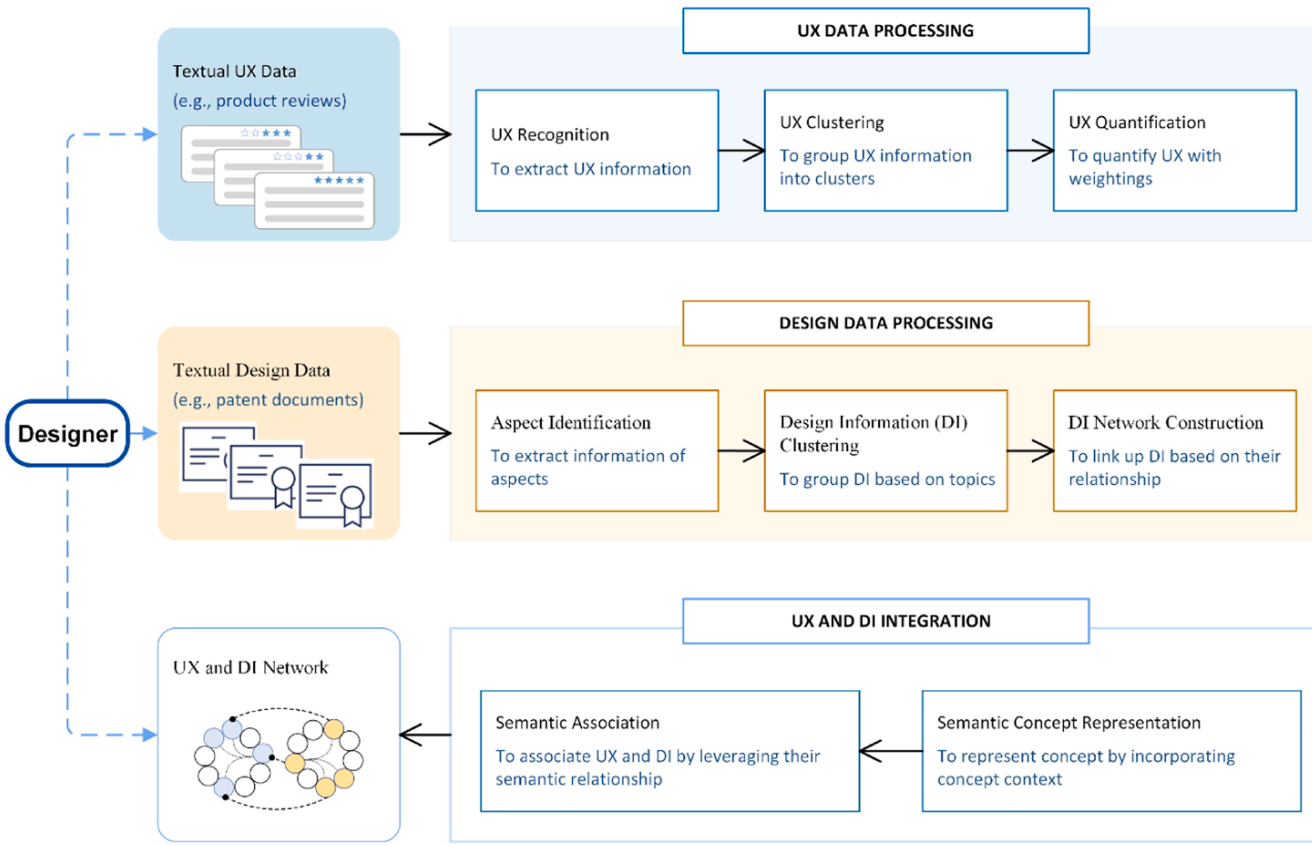

Fig. 4. The framework of the proposed twin data-driven approach for bridging UX and design information.

post-processing uses grammatical features to combine the extracted tokens to form phrases as concept-level information for each aspect, forming a tuple. After the concepts in a sentence are isolated, we need to estimate whether there is a connection between two concepts regarding two various aspects to form the tuple. By using the language context, we use an attention-based LSTM (Long short-term memory) network (Sak et al., 2014) to predict the relationship between two concepts in a sentence to form a concept pair. The concept pairs can then be concatenated based on concepts shared between two pairs to form a tuple. After this UX recognition process is employed in the reviews of the UX dataset, the concept-level UX information scattered in each review can be extracted.

To better understand the extracted UX information from a category perspective, a UX clustering process is designed to categorize concepts of each UX aspect respectively. Based on the BERT representation of each concept, it utilizes the X-means method to cluster the concepts since this method can automatically choose an adaptive number of clusters (Pelleg & Moore, 2000). In the context of UX information, it is difficult to determine the appropriate number of clusters for each aspect due to a large amount of data and the different understandings of certain concepts. Therefore, the clustering approach based on conceptual semantic similarity can give feasible suggestions to a certain extent. Based on the concept clusters, the top *k* frequency terms of a concept cluster can be used as category labels for the cluster.

By using the connections between concepts in tuples and the similarity of concepts within categories, a UX quantification process is designed to measure the importance of each category, so that the proportion of categories and co-occurrence of two categories can be obtained. The importance of each category can be measured by summing up the term frequency of the category. By ranking the quantitative information, it can help designers to prioritize users' preferences.

4.3. Categorizing design information

Several studies have pointed out ontology-based approach contributes to a better and shared understanding of product design ideas (Shi et al., 2017). However, how to build the ontology from design information through computational approaches has been a challenging problem. To extract the key design information and organize it effectively, in our previous study, a design information identification process has been designed to locate and classify candidate language segments in the unstructured design document into predefined aspects, including motivation, solution, and artefact (Liang et al., 2012).

We consider the problem of extracting motivation and solution aspects of design information as a sentence classification problem, which aims to classify the sentences in an archived design document into three categories, including motivation sentences, solution sentences, and neutral sentences. It is noticed that the motivation sentences are often described from a negative viewpoint or have some distinct features by using words like "aim", "desired" and "purpose", while the solutions chosen or proposed are usually expressed from a positive viewpoint to describe the capabilities of solving the problems. For example, as shown in Fig. 2 and Fig. 3, the negative sentences expressing the limitations of the product such as "mixed information" and "the user experience is greatly influenced" are likely to be related to negative user experience, such as "slow" and "delayed" display of text message. The motivations for "fit to hand" and "better viewing" involve the product feature "screen" of a smartphone. This may be linked to the positive UX, such as the "huge size" of the screen. In this case, extracting sentences expressing motivations from design information helps identify concepts that may be linked to UX information, such that the solutions corresponding to the motivation may be related to the UX information as well, and thus the UX information and the technological capabilities may be obtained.

The classifier in this paper BERT-based neural network. It considers the context of a given word, including a wide range of the left and the right context, to capture the semantic features of a word. To capture the language features from the design domain, the BERT model is first pre-trained on a collection of unlabeled design documents. Then given a labelled dataset of sentences, the BERT model is trained to learn the sentence features of three sentence categories. Once its learning process is finished, the model can be used to predict the sentences in the unlabeled set. To leverage the coupling features of concepts, the sentences labelled as neutral and those sentences labelled as non-neutral are kept for the integration process described in Section 4.4.

Then a design information clustering process is designed to group the extracted sentences of motivation and solution into clusters respectively. The motivation sentences of an archived design document compose a short text. Then the topic distributions of the short texts in an archived design document collection can be estimated using the LDA (Latent Dirichlet allocation) model (Blei et al., 2003). The topic words of solution sentences can be similarly obtained. The topic words may be related to possible capabilities from different perspectives, e.g., functional capabilities, and technological capabilities. This process helps identify topics from a collection of sentences regarding the same aspect, which gives an overview of distinct groups of problems and possible capabilities. Then the design information network construction links up design information based on their topic similarity using Jensen-Shannon distance (Tong & Zhang, 2016). Using the topic similarity, the motivation and solution clusters can be formed. The network consists of concepts and their relationships that help designers to search for possible capabilities.

4.4. Integrating UX and design information

From the UX and design information extracted from the previous processing, an integration process is proposed to associate the UX and design information to support product design. To combine the concepts of these two data sources, we need to consider the semantic similarity of the concepts and their context distances. Before measuring the concept similarity, a semantic concept representation is first designed to represent the concepts of UX and topics and concepts of motivation and solution. Word embedding techniques, such as Word2vec and BERT, can be used in the concept representation. A large amount of textual UX data and design data related to a product are collected and processed into paragraphs. Text preprocessing is adopted to build the UX and design dataset respectively, including stop-word removal and tokenization. Then these two datasets are used to fine-tune the BERT model to learn the domain language features. Products, contexts, users, and UX states extracted from UX data and motivations, solutions, and artefacts extracted from design data are considered semantic concepts. These semantic concepts are represented as embedding vectors using the BERT model. The distance between two semantic concepts can be calculated by cosine similarity based on their corresponding vector representation. These semantic distances can be further divided into short-distance, medium-distance, and long-distance relationships by the defined distance ranges.

Then a concept association process is designed to leverage the semantic relationship among concepts to integrate UX and design information so that the design information can be better retrieved from the UX perspective. When zooming out at a category level, the design concepts according to a UX category can be summarized into different topics, which can help provide various perspectives of technological capabilities. For example, the UX about the “huge size” (positive UX state) of the “screen” (product feature) for “business” (situation) may be connected to various design opportunities, such as “flexible folding screen” and “message management method”, where the former one is related to the hardware while the latter one is related the software.

4.5. Case study

We use a case study to demonstrate the feasibility of the proposed approach. We seek opportunities in upgrading the UX for products of “blood glucose monitoring systems” in the healthcare domain. Firstly, we attempt to understand the UX of related products in the market, where we download relevant online reviews and use the proposed UX processing approach to identify the UX aspect, categories, and relevant concepts. Secondly, we search for design documents that are related to the UX aspects by using keywords of product features and situation aspects. Then the design documents are structured and organized based on the proposed model. By associating the concepts of UX and design information at the category level, we can to some extent capture the design concepts that may be possible addressed to the UX.

4.6. UX aspect identification

Two keywords, including “blood glucose” and “monitoring system”, are used as inputs for the crawling process to collect product reviews from Amazon.com. Then the collected reviews are separated into review sentences, which are adopted as the data source of the UX data processing. To train the UX information labelling model, we manually labelled the UX information with several aspects, including product features, activity and environment of the situation aspect, and sentiment term. The trained UX model is then used to predict the label for each word of a sentence, and the segment formation process continues to combine words with relevant labels to obtain meaningful phrases as UX elements.

Fig. 5 shows two product reviews and their corresponding UX information, including product features, situation, UX state, and estimated sentiment score. For example, in the second sentence of review 1, the user mentioned the situation about where he would put the product, i.e., “in my work bag”. Although the product features and UX state were not described explicitly, from the language context, it implies that he referred to the product, i.e., “the monitor”, and may express a neutral opinion for this situation. This “in my work bag” situation is likely to be associated with concepts such as “portable”, “convenient”, and “small size”. When looking at the UX information of these two reviews, it indicates that both users are concerned about “App” features and functions, such as “connected to the app”, “track my number”, “recording my reading”, and the “easy to use” aspect. This structured UX information is easier to understand than the product review in a free text format. This UX information discovery process alleviates designers’ burden on capturing, reading, and digitalizing users’ experiences to obtain meaningful UX information.

The extracted UX information from each product review was further clustered into categories based on their semantic similarity. Table 1 shows some top keywords of UX aspects. We notice that in terms of product features, “contour diabetic app”, “free Bluetooth app”, and “meter app” are related to the software functions catered for the product. When following the connection between product features and situation aspects, we can find that these software functions are often linked to the “activity” aspect, such as “keeps records stored”, “tracks everything on his iPhone”, and “tracking meals and exercise”. It suggests that besides the physical product, users expect some digital services that can provide additional value to the product. In addition, from the “environment” aspect, it also suggests some scenarios in which users typically interact with the product, such as “doctor’s office”, “pocket”, and “travelling”. This may indicate some environmental constraints or potential needs when using the product. Clustering UX information into categories helps designers identify the dimensions from which they can work and provides an overview of the UX information.

4.7. Design information categorization

Regarding design information, we use the patents as a data source to

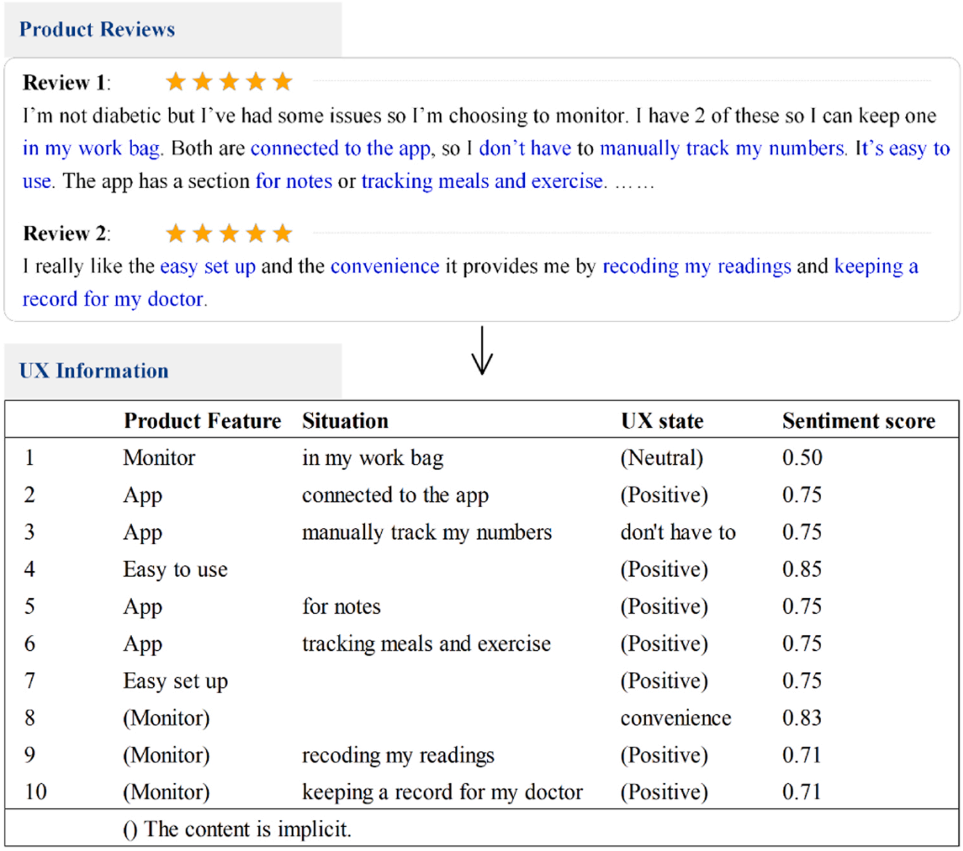

Fig. 5. UX information extracted from product review sentences.

Table 1
Keywords of UX aspects.

Product	Activity	Environment
Contour diabetic app	Reading	Travelling
Free Bluetooth app	Logs all the data	My doctor's office
Meter app	Check-in with my blood sugar	Office
Blood glucose meter	Keeps records stored	Pocket
Smart meter	Pairs with my phone	To my physician
Test strip	Tracks everything on his iPhone	Before or after meals
Easy to use	Tracking meals and exercise	
……	……	……

explore possible design opportunities because patents are widely accessible and valuable resources for designers. Since we focus on a particular product, we need to first limit the scope of candidate design information documents by searching for relevant design documents. We first form the keywords by combining the product name and UX information to get associated concepts not only for "blood glucose monitoring", but also for relevant domains such as "healthcare", "smart technology", and "user interaction". For example, we can use the keywords "blood glucose monitoring" and "track meals and exercise" from the activity category of the situation aspect, and "blood glucose monitoring" and "pocket" from the environment category of the situation aspect. Then the keywords are used as input for the crawling process to download relevant patent documents.

Fig. 6 shows some examples of UX queries, relevant design information from patents, and relevant design topics. When we used query phrases "blood glucose monitoring system" and "tracks everything on his iPhone", we got some patents, such as "systems and methods of multispectral blood measurement" and "intelligent wireless communications for continuous analyte monitoring". By extracting the keywords from the important sections of patent documents, we can obtain their design topics that may be relevant to the design of a "blood glucose monitoring system". For example, for query 1, "measurement methods", "wireless communication", "determining medication dose" and "control system" are likely to the be main technical aspects of this design. When looking at query 2 "manually track my numbers", the corresponding relevant topics involve "sensor method", "biosensor" and "contacting sensor" which are related to the sensing technique, and "smartphone feature" and "control system". It indicates that using similar UX information in a certain category can help to find different topics. After relevant design documents are obtained using various UX queries, the relevant topics can be summarized, which can be viewed as a point worth considering for design innovation.

In addition, we can further look into the detailed design information to gain more insights. Since the most important design concepts are often described in the title, abstract, and description sections of a patent, we extracted these sections as the data sources for the proposed design data processing. To get the important design concepts, the design data are further structured with motivation, solution, and artefact aspects of information by extracting relevant sentences or phrases from the design data. Table 2 shows an example of design information extracted from a patent. It shows that this patent is about "self-monitoring of blood glucose" to develop "optimal diabetes management". To tackle the design problem, some solutions are designed, such as "capable of storing BG readings", "download these readings into a computing device" and "unified platform for monitoring and control". From the artefact aspect, it shows that several features can be explored, such as using "multiple data sources" and "remote monitoring". The design information from solution and artefact aspects helps designers to broaden their insights of technical capabilities that can be applied and extended in their design innovation.

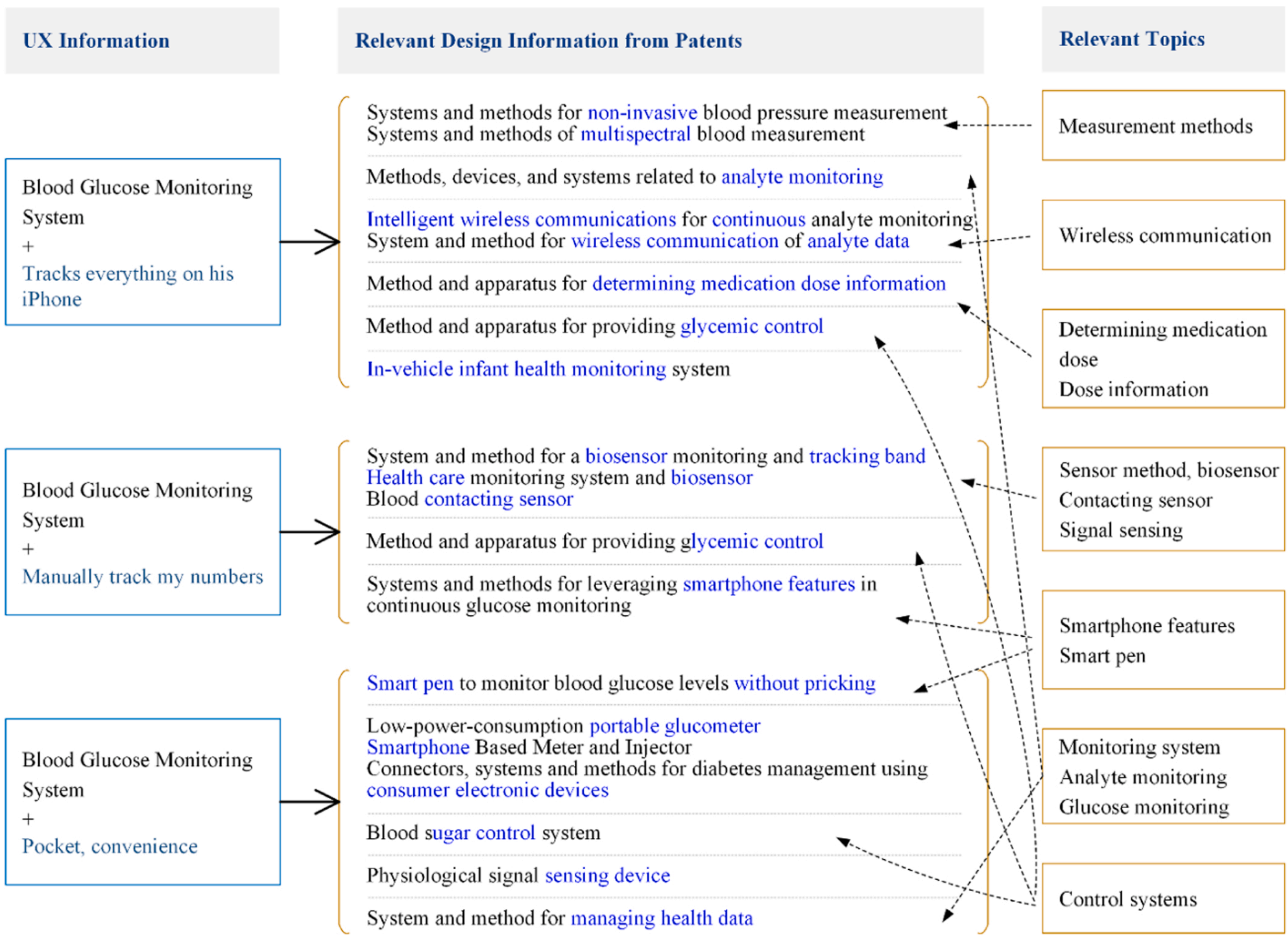

Fig. 6. Relevant design topics extracted from retrieved design information using UX elements as queries.

Table 2
Key categories identified from a design document.

Motivation	Solution	Artefact
Hypoglycemia has been identified as the primary barrier to optimal diabetes management	Capable of storing BG readings (typically over 150 readings)	Multiple data sources
However, the struggle for close glycemic control could result in large blood glucose (BG) fluctuations over time.	Have interfaces to download these readings into a computing device	Multiple data utilization strategies
The optimization of this system depends largely on self-treatment behaviour	Capabilities for basic data analysis	Portable computing devices
Self-Monitoring of Blood Glucose	Unified platform for monitoring and control of blood glucose levels	Remote monitoring
……	……	……

4.8. UX and design information connection

After extracting the UX and design information in a structured format, we built the links between these two sources of information to get design inspiration. Fig. 7 illustrates an example of a UX-based design information network by connecting UX information with design information. As shown in the figure, there are four node types on the UX side, i.e., product, situation, UX state, and user, and three node types on the design information side, i.e., motivation, solution, and artefact. Each node type can include various granularities of information at various levels. The linkages between nodes show that there are connections between concepts or information.

When viewing from the vertical perspective, there are aspect-level, category-level, concept-level, and raw data. Data from the same data sources at the same level can link to relevant concepts or categories if they occur in the same document or sentence. Concepts at different levels can be connected if they shared a certain semantic similarity. For example, on the UX information, both the "meter app" and "free Bluetooth app" at the concept level are linked to the "app" at the category level. Moving from the concept level to the category level gives designers a more abstract description of information while looking from the category level to the concept level gives designers a more detailed description of the information. This provides some interpretation of the UX concepts obtained from a large number of online reviews.

When viewing from the horizontal perspective, the data at the same level but from two data sources can be noticed. Information or concepts from these two data sources are connected based on their semantic similarity and the language context they are surrounded. This indicates these associated concepts to some extent can be considered together to generate creative ideas. For example, both UX concepts "manually track my numbers" and "keeping a record for my doctor" are connected to a design problem about the "barrier to optimal diabetes management". It may suggest that to improve diabetes management, designers can consider some usage contexts, such as tracking daily data and keeping records in a long term for further analysis.

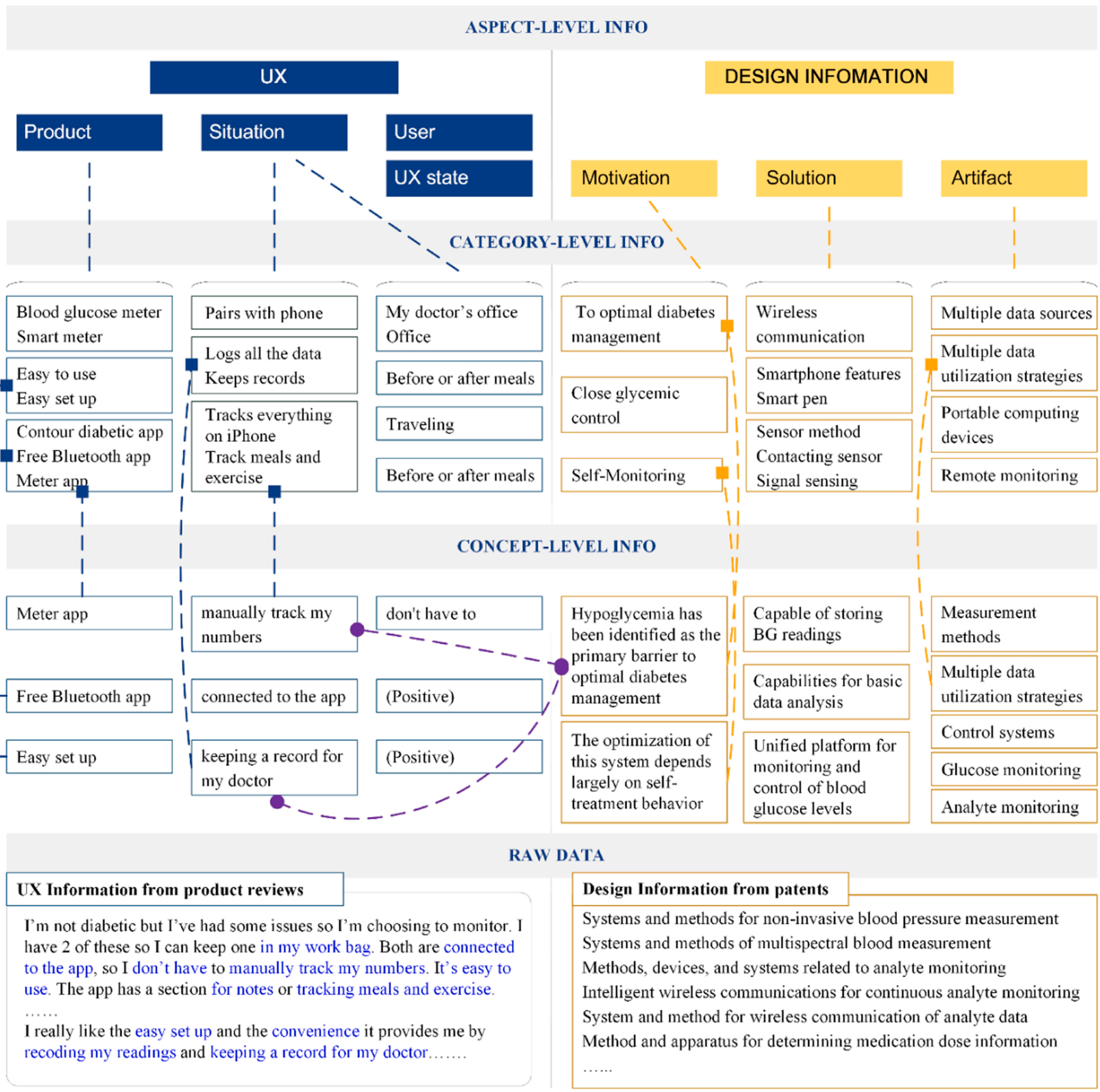

Fig. 7. An illustration of UX-based design information network.

5. Discussion

In recent years, making a great user experience is considered an essential element not only in product design but also in the design of services and ecosystems. In scientific studies and industrial practices, more attempts have been made to capture, understand, and integrate user experience into product and engineering design (Chien et al., 2016; Lin, 2018; Tong et al., 2022; Yang et al., 2019). However, it is time-consuming for designers to manually browse massive amounts of information from online and internal resources to acquire UX-related information. On the other hand, most existing studies on design information management, especially for supporting conceptual design, still mainly focus on function-related design knowledge (Hu et al., 2022). As such, these systems show significant gaps in supporting UX-based design innovation, where little informative association between UX needs and design information is provided to help designers discover UX-related concepts. Built upon the strength of machine learning and NLP, in this paper, a twin data-driven approach to capture and integrate customer insights and relevant design concepts as useful knowledge is proposed.

5.1. Theoretical contributions and implications

This study contributes to the existing literature in three ways. Firstly, different from conventional functional-related representation, our study explores a new way of design information representation to support UX-based design innovation, which is a UX-integrated design information representation to better explore potential technical capabilities from the perspective of user experience. It can integrate different data sources and also provide various granularity of information. In terms of different data sources, it provides multiple perspectives to view heterogeneous data. In this context, starting with a UX element, it is possible to understand what the relevant issues or technical problems are. If looking at an artefact from design information, referencing its relevant issues that also link to the associated UX elements can help to understand that the related solutions can address which user experience. In terms of data granularity, it provides multiple levels of information to view a large amount of textual data, through concept-level information association, category-level of information clustering, and aspect-level of information label. Our representation model presents its ability to suggest multi-dimension UX information with certain technical capabilities. In addition, this multi-dimensional way of information representation can be applied to other data sources for product design, such as functional-based data and UX-based information, by discovering the semantic connections of relevant concepts.

Secondly, our study is one of the few technical attempts to design a twin data-driven approach to bridge UX and design information by exploring smart techniques which encompass data mining, machine learning, sentiment analysis, and network analysis. It provides a systematic approach to extracting and integrating UX and design information by exploiting a large amount of user-generated data over popular e-commerce websites, e.g., product reviews and consumer opinions, and patent documents with rich design know-how. On the one hand, at the document level, our approach can uncover UX elements with fine granularity, e.g., product features, the contexts of use, and consumer feelings, and also extract language segments as concepts for design know-how, e.g., design motivation, solution and artefact features. On the other hand, the extracted segments are clustered based on their semantic similarity using word embedding techniques. To further leverage the power of the proposed UX-integrated design information model, an integration process that associates similar concepts from UX and design information has been designed. This integration helps to form a UX-DI information network which enables the exploration of complex relations among various UX elements and design concepts, e.g., what technical capabilities would be used and suitable for a certain context of use, while these relations are difficult to obtain using the legacy design information management system. In addition, our approach allows designers to search for designed information associated with specific UX. Given UX element combinations, e.g., "blood glucose meter" and "Keeps records stored", our approach can dynamically update the associations between UX elements and design concepts based on semantic similarity.

Thirdly, a case study about healthcare product design is utilized to illustrate how UX and design information can be extracted and integrated for UX-based design and it presents a good and feasible example of using UX insights and technical capabilities based on the integration results. It shows that the twin data-driven approach to building a UX-DI network can capture UX insights, design concepts, and meaningful concept associations from UX and DI data. This UX-DI network can be considered an inspirational source for design idea generation and innovation. Through our approach, large amounts of textual UX and DI information are transformed into a well-structured format that designers can easily access without having to read a large amount of textual data. Furthermore, the capability of organizing the UX and its associated DI information into the concept, category, and aspect levels was demonstrated based on the semantic measure. To assist designers in UX-based design innovation, this multi-dimensional view of information can not only help designers understand customer insights at a fine-grained level but also broaden designers' knowledge space from other perspectives, such as opportunity, technical possibility, and design concepts, which is difficult to achieve in the past. Based on the closeness of semantic measure, our approach also can suggest highly relevant UX and DI information to designers.

5.2. Implications for practice

In most of the literature, product reviews and design documents are two important data sources but they are often considered as isolated data sources for specific product design and innovation activities respectively, such as product reviews mainly for customers' need identification process and design documents for design concept generation activity. However, in practice, designers need to simultaneously search, identify and synthesize useful information from different data sources for optimal solutions. For example, designers may need to know: what customers' needs are; what design problems are to satisfy those needs; and what relevant techniques are for these problems. The approach of integrating these two data sources could then act as an attempt for moving data-driven product design and innovation further. Our study provides fresh impetus for design activities, most helpful in the concept development process, where identifying user experience, exploring technical capabilities, gaining sufficient knowledge, and generating feasible ideas are among the main challenges of UX-based design innovation. This study offers a systematic approach to extracting and integrating user data and design information from massive textual data. It aims to assist designers to tackle the difficulties in existing UX-based product design, in which collecting UX relies heavily on conventional surveys and questionnaires and identifying the relationship between UX and possible technical capabilities counts on manual effort.

By exploring valuable sources of big data and their connections, such as online customer reviews and patent documents, this study aims to gain more insights into UX-based design from various aspects not only regarding the context of use, and user's feelings but also concerning design problem, technology, and design concept. In this regard, the links between heterogeneous data sources are modelled using a UX-DI network and in a multi-dimensional granularity by associating similar concepts. For example, when browsing the UX-DI network built, designers would gain a better understanding of users' preferences and behaviour from the UX side, such as frequent usage contexts and relevant product functions. Then using the associations in the network, designers are further directed to the design problems related to the usage context and their possible solutions. Therefore, designers can use these features as keywords or important concepts and may incorporate some appropriate technology to deliver positive experiences. On the other hand, from the DI side, designers could obtain information about a design problem and its associated user needs. Then the associations in the network would suggest the possible context of use or product functions.

In addition, our study offers qualitative data that can help decision-making, which is modelled using the importance of concepts and concept similarity based on the collective knowledge obtained from big data. Designers can integrate the features and qualitative data into a subsequent design process. For example, after identifying UX needs, possible design concepts, and their associated weights, a quality function deployment (QFD) approach can be inserted into the design concept generation and evaluation process to prioritize the solutions. Moreover, a broad understanding of competitors' product design can be gained as long as their corresponding customer comments and patent documents are available. Such a comparative study can provide designers insights into product planning, strategic design, market differentiation, core function development, and so on.

5.3. Limitations and future research direction

Although encouraging outcomes have been demonstrated, several aspects can be further investigated. In terms of the technical aspect, cutting-edge techniques in machine learning and NLP can be further explored to improve the performance of extracting and clustering UX and DI information as well as semantically integrating UX and DI concepts to build a knowledge graph. One difficulty is that although more labelled data samples have to be collected to further ascertain the effectiveness of the proposed approach, annotating domain information is time-consuming and labour-intensive especially when more products are involved. One possible route is to further adopt a zero/one-shot learning approach to learn the language and semantic patterns of desired aspects or categories using few or zero training data, but leveraging large general knowledge from relevant data sources.

Additionally, this paper focuses on textual data in terms of multiple levels of granularity. It would be interesting if other kinds of design information, such as sketches and images semantically related to relevant concepts could be incorporated into the design knowledge network. Based on our UX-integrated information representation model, one possible way is to connect textual concepts and images by learning visual concepts from natural language supervision (Radford et al., 2021). This would be helpful to provide a more vivid impression to aid data-driven UX-based design and innovation. Moreover, although our case study has demonstrated that our model can uncover UX and DI concepts directly from online reviews and patents and form a UX and DI network to assist design concept generation, we expect some studies can be further explored, such as what design activities our approach can support, e.g., opportunity identification and technical trend analysis, and how the information discovered can be analyzed, interpreted and visualized and interacted with. In addition, understanding what users do with the algorithm/systems is also important to optimize the algorithm to perform effectively (Shin et al., 2020). In the future, we will try to further study how designers search, organize and use information from different sources to better improve what our algorithms can provide. Another opportunity is to involve designers in the process of designing the system to better understand their needs (Dwivedi et al., 2021).

6. Conclusions

In this paper, we have built a twin data-driven network to associate UX and design information based on machine learning and text mining to capture the concept, category, and aspect levels of information from web product reviews and design documents. The extracted information grouped at different levels was considered useful resources to help designers to generate creative ideas to identify design opportunists. In addition, designers can easily obtain this conceptual knowledge and design know-how without reading and digesting a large number of textual data. The proposed approach helps designs to grasp the latest information over time. Moreover, the feasibility of organizing information at different levels was demonstrated using a case study. Designers can get general ideas of the overall data and go into details of a specific design solution. In the future, we will explore how the design information collected from various sources with heterogeneous structures can be organized and develop a knowledge system based on the proposed UX-integrated design information network to assist design activities.

Acknowledgement

The work reported in this paper was supported by the Natural Science Foundation of Chongqing (No. CSTB2022NSCQ-MSX1565 and CSTC2020JCYJ-MSXMX0864).

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